UNIVERSITEIT GENT
FACULTY OF ECONOMICS AND BUSINESS ADMINISTRATION

Determinants of International Migration

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Supervisor: Prof. Dr. Glenn Rayp (Ghent University)

Submitted at Ghent University,

To the Faculty of Economics and Business Administration,

In fulfillment of the requirements for the degree of Doctor in Economics

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1

Introduction

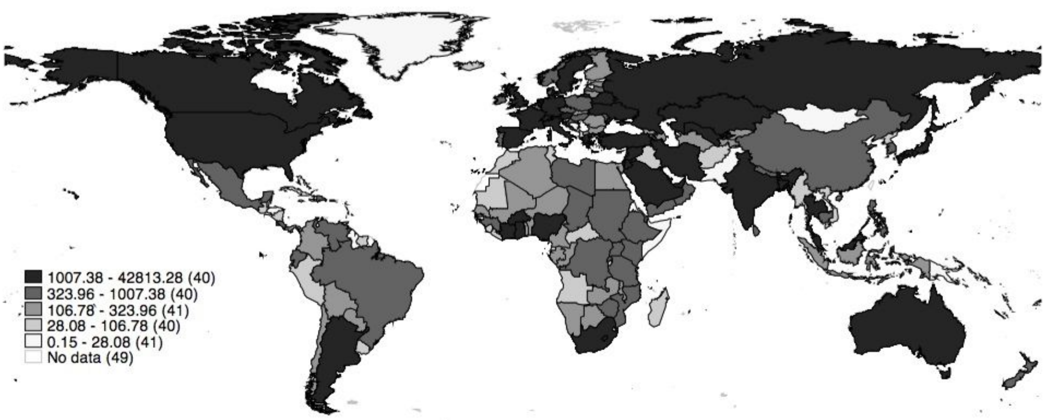
1.1 Motivation and orientation

Migrations have occurred throughout human history. The first wave of migration can be traced back to roughly ninety thousand years ago, when Homo sapiens ventured out of Africa to colonize the world. Ever since, humans have been constantly on the move, crossing boundaries and oceans in search of greater well being. Today, people inhabit virtually every corner of the world. The pace of migration considerably accelerated in the eighteenth and even more so in the nineteenth century, related in particular to involuntary slave trade and industrialization, respectively. In the face of rising globalization, new migratory streams were encouraged by overpopulation, new economic opportunities in industrial centers and improved transportation techniques. Later on, also the First and Second World Wars as well as the genocides and crises they gave rise to had an enormous impact on international migration. Post-war economic expansion as well as the fall of communism and the breakup of the Soviet Union formed yet another stimulus for immigration under the form of active labor recruitment in the OECD and immigrant flows prompted by shifted borders. Recently, the expansion of immigration from Central and Eastern Europe to Western Europe following the enlargement of the European Union has been apparent, but also migration from India and China to non-European countries has been growing at a steady pace.

Given the upsurge in the last few decades, more people are on the move today than at any other point in time. According to the United Nations, the number of international migrants was estimated at 214 million (3 percent of the world population) in 2010. The International Organization for Migration estimated that if migration keeps growing at the same pace as the last 20 years, the stock of international migrants worldwide could reach 405 million in 2050. Demographic forces, globalization, environmental change and technological revolutions are expected to further intensify migration pressures both within and across borders.

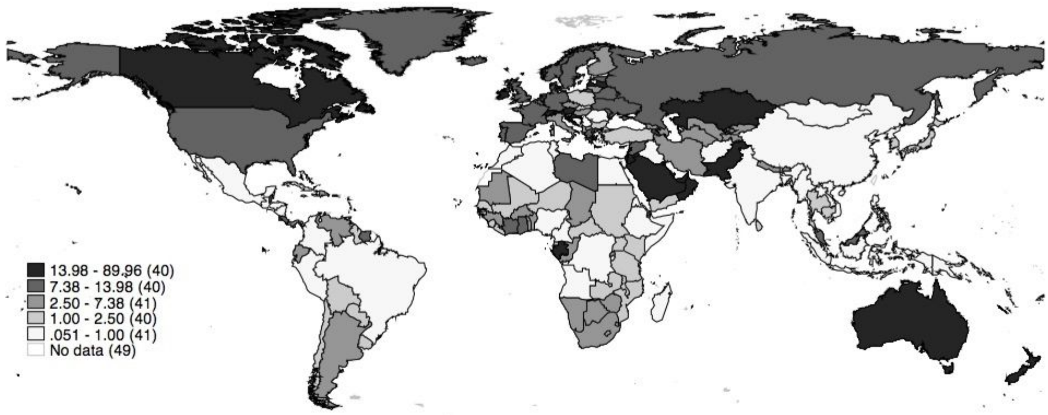
Figure 1.1 offers a first glimpse at the composition of the global migrant stock across countries in 2010, ranging from 150 immigrants in Tuvalu to 43 million in the United States. Especially Western Europe and New World countries such as the United States, Canada, Australia and New Zealand but also Argentina, South Africa, the Persian Gulf states, the former Soviet Union and India appear as important destination countries. Not surprisingly, migration remains fairly limited for small island states located mostly in the Pacific or the Caribbean. Focussing on the migrant stock as a share of the population, on the other hand, significantly alters the picture, as can be seen from Figure 1.2. The proportion of immigrants ranges from 0.5 percent in Indonesia and China to 70 percent in some island states and in the oil-rich Persian Gulf countries Kuwait and Qatar. An illustration of the most recent migratory movements, based on net migrant flows, finally, can be found in Figure 1.3. Although the picture reveals a great deal of persistence in migration patterns (migration to the New World, Western Europe and Russia is still apparent), it also brings to light how some countries have evolved as new settling destinations (such as Singapore and Liberia) or net emigration countries (India and Bangladesh).

Figure 1.1: International migrant stocks (thousands), 2010



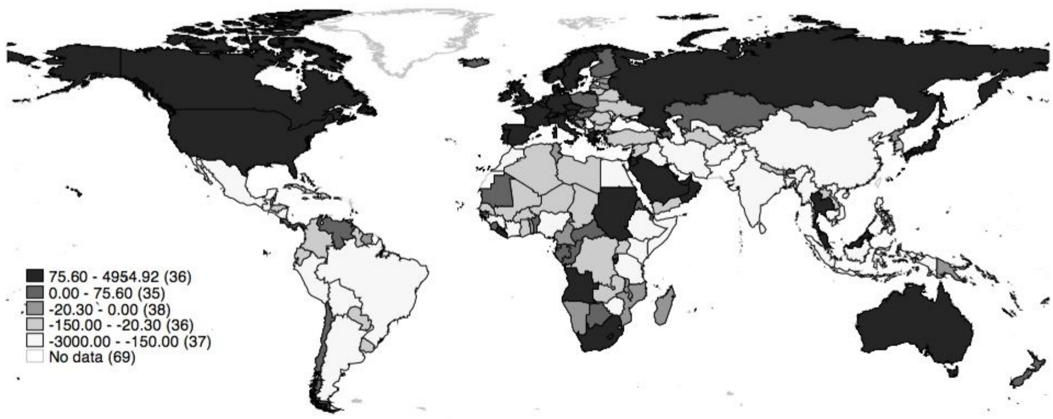
Source: Authors' calculations based on Global Bilateral Migration database, World Bank (2011)

Figure 1.2: International migrant stocks (% of the population), 2010



Source: Authors' calculations based on Global Bilateral Migration database, World Bank (2011)

Figure 1.3: Net international migrant flows (thousands), 2010



Source: Authors' calculations based on Global Bilateral Migration database, World Bank (2011)

These figures are however unilateral in nature and cannot tell us anything about the origin of migrants or changes in the composition of the migratory streams towards these countries of destination. The World Bank's recently constructed Global Bilateral Migration Database, on the other hand, provides a comprehensive picture of bilateral migrant stocks over the last half of the twentieth century. Although more recent data are not available as of today because the 2010 round of censuses is still being conducted in a number countries, these data allow for a more thorough analysis of the evolution of global bilateral migration between 1960-2000.

Table 1.1 presents an overview of regional migrant stocks during this period. Several interesting patterns emerge. The total number of immigrants worldwide increased from 93 to 167 million between 1960 and 2000. As a share of the population, however, the immigrant population fell from 3.05 percent to 2.71 percent (not reported in the table). Not surprisingly, migration towards high income OECD countries appears as the most important component of global migration in all decades and has been growing at a steady pace, reaching 87 million immigrants in 2000. The most spectacular rise, however, is obtained for migration towards high income nonOECD countries which nearly quintupled over the period considered. Also migration in the Middle East and North Africa, which represented only a limited share of global migration in the 1960s, rose significantly due mainly to increasing migration to the oil-rich states in the Persian Gulf. Latin America and the Caribbean as well as South Asia, on the other hand, are the only regions where emigration exceeds immigration, resulting in falling migrant stocks. The latter can primarily be related to rising migration from Latin America and the Caribbean to the United States and return migration between India, Pakistan and Bangladesh in the aftermath of the partition of India. This can be seen from the lower panel of Table 1.1, which illustrates how also the origin of global migration has shifted through time. In all decades, migration within the Soviet Union (and former Soviet Union) accounted for a significant share of global migration, turning Europe and Central Asia into the most important sending region in 2000. Yet, the largest growth rate is recorded for Latin America and the Caribbean, which sent out 8 times as many immigrants in 2000 compared to 1960. Also the proportion of immigrants born in high income OECD countries appears significant, though the majority of this migration is intraregional and especially consists of migration to the United States or between Western European countries.

Table 1.1: Evolution of global migration by region 1960-2000

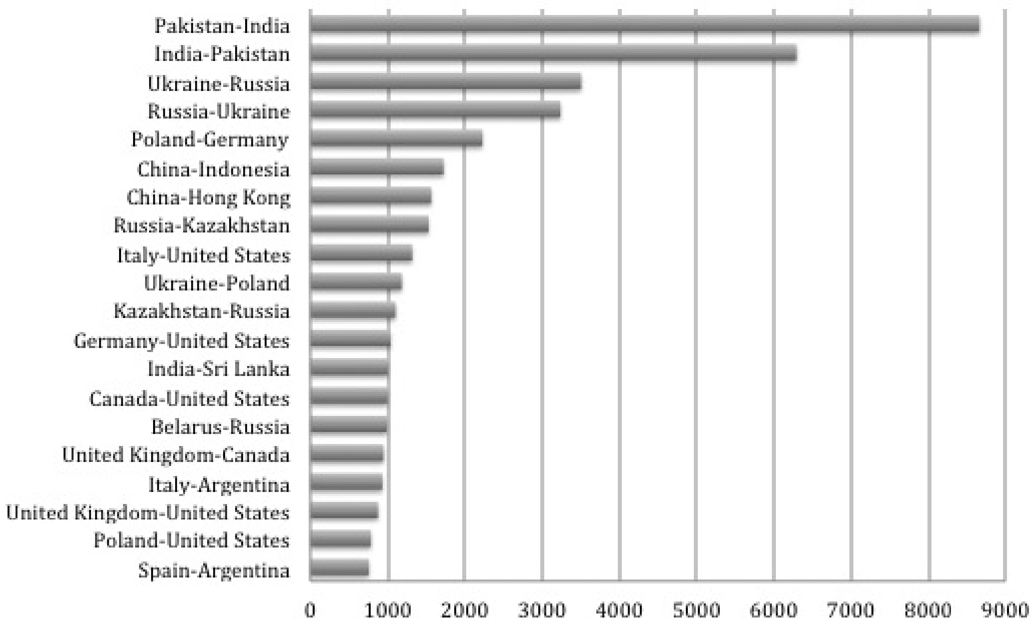
	Migrant stocks					Growth (%)
	1960	1970	1980	1990	2000	1960-2000
By destination region						
East Asia & Pacific	3655822	3507395	2214187	2305491	3828336	4.72
Europe & Central Asia	18447696	23261124	25622610	30321787	27529855	49.23
Latin America & Caribbean	5963653	5395582	5526238	5428259	5854820	-1.82
Middle East & North Africa	2231489	1877964	2503756	3819290	4906973	119.90
South Asia	17822916	16448529	14731586	12509669	10937668	-38.63
Sub-Saharan Africa	7821666	8282304	9110177	9125721	11197899	43.17
High income nonOECD	2881541	3963301	7464599	13136647	16200117	462.20
High income OECD	34246035	43053140	53004756	65211046	86611554	152.91
By origin region						
East Asia & Pacific	6332458	4741602	8091469	11515329	16743689	164.41
Europe & Central Asia	22775632	28172570	31945716	39348742	39370881	72.86
Latin America & Caribbean	2911019	4518607	8397514	13643199	23494679	707.09
Middle East & North Africa	3021042	4937287	7589394	10505852	11906043	294.10
South Asia	18658537	17879024	18020386	19027946	21057969	12.86
Sub-Saharan Africa	6139441	7379870	9138830	10394368	13727895	123.60
High income nonOECD	1591982	3977139	2960212	4207693	5270912	231.09
High income OECD	31640707	34183240	34034388	33214781	35495154	12.18
World	93070818	105789339	120177909	141857910	167067222	79.51

Source: Authors' calculations based on Global Bilateral Migration Database, World Bank (2011).

Also at the country level, important changes in the composition of migrant stocks can be noted. Figures 1.4 and 1.5 depict the 20 most important bilateral migration streams for 1960 and 2000, respectively. The former illustrates how in the 1960s, the largest proportion of the global migrant stock could be linked to the mass migration following the partition of India as well as intraregional migration between countries of the former Soviet Union, East and South Asia and Western European migration to the United States. In the subsequent decades, the United States appear as the most important destination for immigrants from no less than

60 countries, housing around one fifth of the world's migrant population. Figure 1.5, on the other hand, demonstrates how more recent migration is shaped predominantly by flows from developing countries to the United States and Western Europe, signaling the impressive growth of South-North migration at the end of the twentieth century. Whereas most migration in the 1960s, apart from migration within the Soviet Union, originated in Europe and South Asia, recent immigrants are now born also in Latin America, East Asia, North Africa and the Middle East. Although in 2000, migration to Western Europe largely remains stemming from elsewhere in Europe, the number of Chinese immigrants in the United States is more than twice the size of any other bilateral migrant stock in the database. This changing composition also reflects the destination country's willingness to accept immigrants from ever more diverse backgrounds (see Özden et al., 2011).

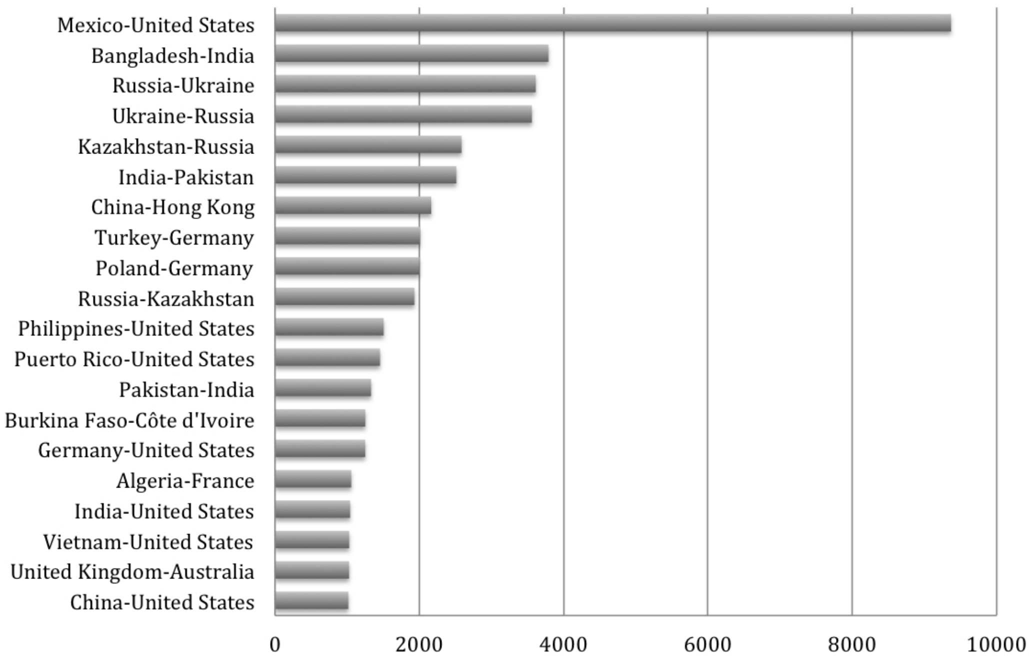
Figure 1.4: Top 20 destinatin-origin migratory streams (thousands), 1960



Source: Authors' calculations based on Global Bilateral Migration database, World Bank (2011)

The diversification can also be observed from the decomposition of global migra-

Figure 1.5: Top 20 destinatin-origin migratory streams (thousands), 2000



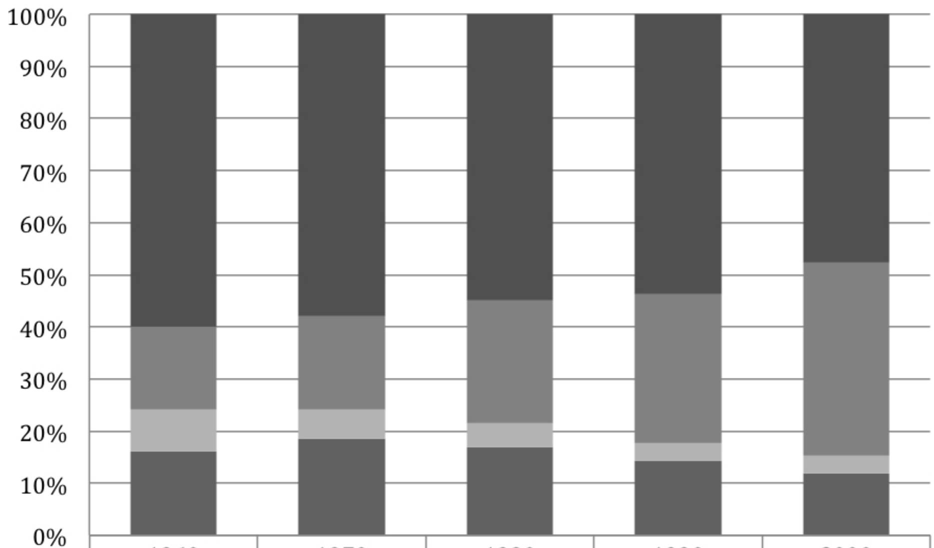
Source: Authors' calculations based on Global Bilateral Migration database, World Bank (2011)

tion between the North and the South.[1] Figure 1.6 designates South-North migration as the fastest growing component during the period whereas North-North, North-South and South-South migrations all constitute declining proportions of global migration. Specifically, the data suggest that the migrant stock born in the South and residing in the North more than quadrupled between 1960 and 2000, i.e. many times faster than the global migrant stock which rose by 80 percent in the period. With 62 million migrants in 2000 (37 percent of the global migrant stock), South-North migration can as such be considered the main driver of global migration. In absolute numbers, however, South-South migration remains the most important category accounting for nearly 80 million immigrants. It rose

[1]We follow Özden et al. (2011) who classify Australia, Canada, Japan, New Zealand, the United States, the EU-15 and the European Free Trade Association as developed countries, the remaining countries being classified as developing.

by 13 million between 1990 and 2000, i.e. the second largest increase following South-North migration. By 2010, however, South-North migration is estimated by the United Nations to have overtaken South-South migration. In some regions such as Sub-Saharan Africa (SSA), nevertheless, the extent of South-South migration (69 percent of SSA migration based on the 2000 census) still goes beyond that of South-North migration. Most of these migratory streams are intraregional, with the exception of significant interregional migration from developing countries in the Middle East, North Africa and Southeast Asia to the Persian Gulf states.

Figure 1.6: Migration between the North and the South



	1960	1970	1980	1990	2000
South-South	55811853	61210147	65913784	76212423	79706337
North-South	14699111	18985153	28494312	40387275	61799175
South-North	7540549	5993179	5568285	5127350	5677796
North-North	15019305	19600860	20201528	20130862	19883914

Source: Authors' calculations based on Global Bilateral Migration database, World Bank (2011)

The pressures of human migrations, whether as prehistoric settlements, colonization or modern international migrations, have affected population structures and characteristics, social and cultural patterns, economic development and physical environments in both the places they leave and those they settle in. As people move, their cultural traits and ideas diffuse along with them, creating both new opportunities (through the exchange of cultural experience and knowledge) and social tension (for example between majorities and minorities, leading to local struggles, racism and even criminality) at home and abroad. Also their choice of location within the destination country has a significant impact on the location choice of natives, their perception of immigrants and the integration of the latter. Yet, international migration is inevitable and offers enormous potential benefits for migrants themselves as well as for countries of origin, destination and transit. While developing countries might have to deal with a brain drain of their most educated, they can enjoy remittances sent home by their expatriates as well as transnational networks as a source for the exchange of expertise, foreign exchange, overseas marketing openings and political support. For developed countries, on the other hand, international migration might be considered part of the solution for labor shortages and population aging. Supported by the right policies, international migration can thus be highly beneficial for the development of both countries of origin and destination and for the immigrants themselves. Yet, in order to reap these benefits and design and implement sound policies to manage migration, a clear understanding of the forces that drive migration patterns is important.

The first academic research on migration goes back to the late nineteenth century, but the motivations for migration gained renewed attention in the 1980s. Ever since, the need for comprehensive and consistent data on migration has become widely recognized. Whereas earlier studies were restricted to analyze migration patterns from a unilateral perspective, i.e. without knowledge of a migrant's origin or destination (often using national statistics or United Nations estimates), more recent surveys predominantly use data on bilateral migration flows, allowing for a much richer analysis. In fact, the main focus of the empirical literature has been on the principal channels of mass migration to Europe and the OECD in the twentieth century. Governments in these countries typically started some decades ago to keep track of the number of immigrants residing and/or arriving in their countries. This allowed intergovernmental organizations such as the European Union, the OECD and the World Bank to compile the data from national sources (usually population registers and census data) into open access databases describing bilateral migration between member states or countries worldwide. The OECD's International Migration Database, for instance, provides annual series on migration flows and stocks for most member states and for the most recent years (in general 1990-2007). The World Bank's Global Bilateral Migration Database, on the other hand, combines census data and population registers to construct decennial matrices of global bilateral migrant stocks corresponding to the period 1960-2000. An important advantage of this global bilateral database is that it allows for a separate analysis of South-North and South-South migration. Moreover, bilateral data in general contain more information than unilateral data which allows for a more rigorous analysis of the determinants of migration. An empirical analysis based on bilateral data reduces the risk of biased results because it permits the inclusion of bilateral or country specific dummies to control for unobserved heterogeneity.

In order to get an understanding of the driving forces shaping migration patterns across countries and within destinations, this dissertation investigates the determinants of bilateral international migration and the location choice of immigrants with particular attention to a number of methodological challenges and for various geographical regions, i.e. migration to the OECD, migration between SSA countries and immigrants' location choice in Belgium.

In what follows, we present an overview of the most important migration theories (Section 1.2), the stance of the recent empirical literature (Section 1.3) and methodological issues that arise (Section 1.4). Section 1.5 elucidates the outline of the following chapters in this dissertation and illustrates how each of these address some of the methodological issues described in Section 1.4 as well as how they contribute to the literature.

1.2 Migration theories

To this day, a comprehensive theory of international migration does not exist. In the last century, several competing theories have been developed. Although economic forces have often been pointed out as the root causes for international migration, the literature gradually integrated also other societal aspects to explain prevailing migration patterns. An overview of the most influential migration theories is presented below. It largely draws upon the well-cited and excellent literature review on the determinants of migration presented in Massey et al. (1993).

1.2.1 Ravenstein's Laws of Migration

At the end of the nineteenth century, in response to William Farr's (1876) remark that migration seems to continue without any definite rule, Ernst Ravenstein wrote his famous Laws of Migration (1885, 1889). At the heart of Ravenstein's migration theory are the concepts of absorption and dispersion. A country of absorption is one in which the population gradually increases (more people are entering than leaving), while a country of dispersion is defined as the reverse. A thorough observation of census data in the UK (in the 1885 study) and later in over twenty other countries (in the 1889 study) resulted in seven so-called 'laws of migration'. Two of those are relevant for this introduction: migration is (i) primarily driven by economic reasons and (ii) decreasing with distance. Remarkably, nearly a century later, most of Ravenstein's laws still stand. In fact, Lee (1966) developed a general framework for explaining various types of spatial movements, which allowed him to reformulate Ravenstein's laws in a more rigorous fashion. He remarked that since the work of Ravenstein, few studies had considered the reasons for migration and as such little progress had been made in understanding the process behind it. As a starting point for his analysis, Lee (1966) formulated a more general definition of migration than the one usually applied until then: he defined migration as any permanent or semi-permanent change of residence. There are no restrictions upon the distance of the move or upon the voluntary or involuntary nature of the act, and no distinction is made between internal and international migration: "No matter how short or how long, how easy or how difficult, every act of migration involves an origin, a destination, and an intervening set of obstacles" (Lee, 1966). He postulated that migration is driven by push factors (unfavorable conditions in the origin country), pull factors (attractive features of the destination country), intervening obstacles and personal factors.

Through the years, Ravenstein's laws have greatly stimulated research on the determinants of migration. Several theories have been developed to explain the origin and nature of migration. The most important are summarized below.

1.2.2 Neoclassical migration theories

The migration theme regained attention from the academic world in the second half of the twentieth century due to the development of the neoclassical macro-model of migration (Lewis, 1954; Ranis and Fei, 1961; Harris and Todaro, 1970; Todaro, 1976). This theory postulates that migration occurs because of geographical differences in labor demand and supply. In this light, countries where labor is abundant relative to capital will have a low equilibrium wage, while countries where labor is relatively scarce will be characterized by a high market wage. Consequently, rational workers have an incentive to migrate from low-wage to high-wage countries. This simple macroeconomic explanation of international migration considerably influenced public thinking and provided the intellectual basis for many immigration policies (Massey et al., 1993).

Analogously, neoclassical theorists developed a microeconomic model of individual choice (Sjaastad, 1962; Todaro, 1969; Greenwood, 1975; Todaro, 1976; Todaro and Maruszko, 1987; Todaro, 1989). According to this theory, the rational individual maximizes its utility subject to a budget constraint. People move to where they can be most productive, given their skills, and earn the highest wages. As such, the neoclassical migration theorist views migration as some kind of investment in human capital. One of the most influential migration models in the literature concerns the one developed by Todaro (1969) and Harris and Todaro (1970) to explain rural-urban labor migration. The model was originally intended to explain continuing rural-urban migratory moves in developing countries despite rising unemployment in cities. In order to explain this apparent contradictory phenomenon, the authors suggested to reconsider the simple wage differential approach by focussing on expected rural-urban income differentials, defined as the product of wages and employment rates, instead. As such, the Harris-Todaro model was the first to take into account the probability of finding a job upon arrival in the destination. Hence, in contrast to the macroeconomic literature, the microeconomic theory of international migration does not assume full employment. Rather, the migration decision is based on the comparison of the net present value of lifetime earnings across alternative locations. The latter is defined as the discounted value of the difference between expected income gains and costs of migration (both monetary and psychological) such as the cost of transportation, the effort involved in learning a new language and culture and in leaving one's roots. A person is expected to migrate if the net present value of the expected gains from migration is positive.

Another important contribution concerns the migration model developed by Borjas (1989), which translates the Harris-Todaro model for internal migration into one that explains international migration streams through the concept of an international migration market. Specifically, the migration decision is based on the comparison between discounted expected payoffs and costs of migration to alternative international destinations. Aggregate migration flows between countries are then simply the sums of individual moves undertaken on the basis of individual cost-benefit estimations. Not unimportantly, Borjas (1989) argued that also non-economic factors such as the country's political orientation, its education level and immigration policy have an impact on the size of migration and should be included in the migration equation.

This remark in fact highlights one of the major criticisms against the neoclassical micro-level migration theory, namely that it relies on the assumption of perfect markets and perfect information. This is hardly realistic, given that most markets are typically far from perfect and that it is very unlikely that immigrants have perfect knowledge of the costs and benefits of migration (De Haas, 2010). Given its focus on expected incomes, the neoclassical migration model is unable to explain actual migration patterns, which cannot be seen in isolation from the social, cultural, political and institutional context in which they take place. Neither can it deal with constraining factors such as immigration policies putting governmental restrictions on migration.

1.2.3 Alternative migration theories

Alternative theories to the macro-level neoclassical migration theory are the dual labor market theory and the world systems theory. According to the former, migration has nothing to do with individual or household decisions but follows from the inherent labor demands of modern industrial societies. As such, Piore (1979) argues that international migration is completely demand-driven. Contrary to the neoclassical theory of migration, wage differentials are neither a necessary nor a sufficient condition for labor migration to occur. The world systems theory, on the other hand, views the world as a complex network of economic exchange relationships (Mabogunje, 1970; Wallerstein, 1974; Petras, 1981; Portes and Walton, 1981; Castells, 1989; Sassen, 1988, 1991; Morawska, 1990). Wallerstein (1974) postulated that not the duality of the labor market but the bifurcation of the world economy related to the penetration of richer, industrial, capitalist economies (core) in poorer, undeveloped nations (periphery) lies at the heart of international migration.

Critiques against the neoclassical micro-level migration theory concern the fact that immigration is not necessarily an individual decision, but should rather be placed within the broader context of the family or community. In this regard, the 'new economics of labor migration' theory argued that the migration decision is part of a family or household strategy rather than an individual decision. This larger integrated unit seeks to not only maximize expected earnings, but also to insure against income and productivity risks stemming from imperfect market environments (Stark and Levhari, 1982; Stark, 1983; Taylor, 1984; Stark and Bloom, 1985; Katz and Stark, 1986; Lauby and Stark, 1988; Stark and Taylor, 1991). Besides the focus on absolute income differentials - inherent to the neoclassical human capital model - this theory also recognizes the importance of relative income considerations. Specifically, the new economics of labor migration postulates that a wage differential is not a necessary condition for international migration; households may have strong incentives to diversify risks through transnational movement even in the absence of wage differentials (Massey et al., 1993).

1.2.4 The push-pull framework

Although most of these theories posit initially widely differing explanations for migration, they do not necessarily contradict each other. While their initial assumptions and hypothesis might be very different, they can be interpreted to simply act on different levels of aggregation. Yet, as put forward by Papademetriou (1991), it is perfectly possible that individuals engage in cost-benefit calculations; that households act to diversify labor allocations; and that the socioeconomic context within which these decisions are made is determined by structural forces operating at the national and international levels. Besides, current trends and patterns in migration reveal that a full understanding of contemporary migratory processes will not be achieved by relying on the tools of one discipline alone (Massey et al., 1993). Whereas in most of the academic literature, economic motivations have provided the dominating explanation for international migration, they do not seem able to fully explain actual migration patterns. This shortcoming raised attention for the role of social, political, cultural and environmental factors as well as demographic pressure and geographical proximity. These potential driving forces of migration can however easily be integrated into the existing economic theories of migration, through the use of a push-pull framework.

The latter, apparently the most popular migration model, was developed by Lee (1966), although he did not use this exact terminology (Passaris, 1989). In this model, immigrants are pushed away from their original location due to its undesirable characteristics and pulled towards a specific destination because of its attractive features. As such, all factors defining characteristics in the home country are considered push factors while those in the host country are regarded as pull factors. These factors may reflect any aspect of society: sociological, geographical, political, environmental and cultural factors are all expected to initiate migration streams alongside the obvious economic determinants. Analogous to the micro-level neoclassical migration model, the push-pull model is an individual choice model but, contrary to the neoclassical approach, it is able to integrate other theoretical insights and has therefore frequently been recommended as the ideal framework for analyzing international migration (Bauer and Zimmermann, 1998; De Haas, 2010).

An application of the push-pull framework makes use of Newton's law of gravity to explain the size of migration flows between two locations: "Any two bodies attract one another with a force that is proportional to the product of their masses and inversely proportional to the square of the distance between them". Drawing on the success of the gravity model to explain international trade patterns developed by Tinbergen (1962), Karemera et al. (2000) adapted the model to the context of migration patterns. Migration between two locations (bodies) is expected to positively depend on their populations or gross domestic product (mass) and the distance between them. The traditional gravity model is often extended by including also other characteristics of the origin and destination countries potentially encouraging migration (see e.g. Karemera et al., 2000; Lewer and Van den Berg, 2008).

1.2.5 Migration persistence models

The general push-pull framework is static in nature, in the sense that it explains only the initiation of migration but not its prevailing perpetuation. As pointed out above, migration may be initiated by a variety of reasons: individuals chasing higher income; households searching to diversify risks; employers in industrial countries recruiting from abroad to satisfy their permanent need for labor; inhabitants of peripheral regions moving after the core disturbed their economic structure through the penetration of their markets; or a combination of the above. But nothing indicates that the conditions which initiate the transnational movement are the same as those that perpetuate it across time and space. As suggested by Massey et al. (1993), wage differentials, relative risks, recruitment efforts, and market penetration may continue to cause people to move, but the act of migration also generates conditions which themselves turn out independent causes for new migratory streams. Theories of the perpetuation of international migration are able to explain why migration to a certain destination might persist even if the initial incentive for migration has disappeared. As such, migration processes develop their own momentum once they have started, making additional movement in the future more likely, a process Myrdal (1958) called cumulative causation (Massey et al., 1993).

The most important source of persistence concerns the presence of social networks in the destination country, which add a dynamic perspective to the migration decision. Nelson (1959) was the first to emphasize the role of prior migrants in influencing settlement patterns of subsequent migrants. This type of migration is often called 'chain migration' because it might be seen as a self-sustaining diffusion process. New migrants are attracted to destinations inhabited by friends or relatives who moved there before. The larger the network of interrelated individuals in the host country, the lower the costs and risks of migration. Having friends and relatives in a receiving country not only reduces the psychological costs of migration (the costs involved in cutting old ties and building new ones); they also have an impact on the monetary costs of the move (family and friends can help to arrange transport and offer temporary accommodation) and the expected returns to migration (by offering assistance to find a job upon arrival). Over time this process spreads outward and motivates larger segments of the sending society to move (Hugo, 1981; Taylor, 1984; Massey and Denton, 1987; Massey, 1990a,b; Gurak and Caces, 1992).

Other theories aimed at explaining the continuation of migration concern the institutional theory of migration, the theory of cumulative causation and the migration systems theory. The first theory argues that as migration between countries occurs on a larger scale, institutions step in devoted to the arrival and integration of successive waves of immigrants. As these private and voluntary organizations become known to migrants, they comprise another form of social capital which reduces the cost of migration and thus increases the propensity to migrate. This gradual build-up of institutions generates a flow of migrants which becomes more and more institutionalized and independent of the factors which initiated it (Massey et al., 1993). The theory of cumulative causation, originally developed by Myrdal (1958), posits that once the migration process has started off, it changes the economic and social context in which subsequent migration decisions by individuals or households are made (Stark et al., 1986; Taylor, 1992; Massey et al., 1993). The migration systems theory, finally, can be considered a generalization of the theories previously described. It incorporates the theory of cumulative causation in the sense that it takes into account changes in demographics and in the political, social and economic conditions caused by international migratory moves. As such, the network theory and institutional theory of migration can be seen as two examples of how international migration modifies prevailing conditions in an international migration system. Yet, it goes even further by also considering changes in the political, demographic, economic and social context which cannot be related to international migration. Specifically, an international migration system consists of a group of receiving countries that are linked to a set of source countries by relatively intense flows and counterflows of goods, capital and migrants. As such, the countries in the migration system are not only linked by exchanges of people but also by other types of linkages (Fawcett, 1989). Kritz and Zlotnik (1992) distinguish four of them: historical, cultural, colonial and technological linkages, all of which are allowed to change across time and space.

Nonetheless, although these dynamic models of international migration initially rely on very different initial assumptions compared to the traditional push-pull model of migration, the latter does not prevent these sources of persistence from being included in the empirical model. Both social networks and migration-encouraging institutions as well as the broader societal factors and linkages can easily be integrated into a push-pull framework for migration.

Although most recent utility based models of international migration control for the impact of social networks in the migration decision, Hatton (1995) goes even further by building in two dynamic components in the neoclassical model of migration. The model introduces uncertainty in the migration decision and accounts for the formation of expectations about future income streams based on past information. This approach has two important implications. First, both the changes and the levels of the explanatory variables enter the model separately. This makes it possible to distinguish between short-run and long-run determinants of migration. Second, the estimation equation includes both the lagged dependent variable and the migrant stock. The simultaneous inclusion of these variables forms one of the major methodological issues discussed below.

1.3 Empirical literature

1.3.1 Migration to the North

As mentioned in the introduction, the main focus of empirical research on the migration determinants has been on the principal channels of mass migration in the twentieth century. These include both North-North migration, such as European migration to North America or Australia, as well as South-North migration, such as migration from former colonies to Europe and migration in the context of guest worker programs and exile.

Specifically, due to data limitations, most studies have estimated the determinants of international migration to a single destination country, either ignoring the origin of migrants, i.e. pure time series models with time as the only dimension (see e.g. Hatton, 1995) or accounting for the origin of migrants using a two-dimensional panel data model with bilateral effects (Karemera et al., 2000 for immigration to Canada and the US or Vogler and Rotte, 2000; Fertig, 2001; Boeri et al., 2002; Brücker and Siliverstovs, 2006 for the German case). The recent availability of comprehensive panel data on bilateral migration offers a three-way panel dataset which allows for the inclusion of both bilateral effects and time dummies. This has the important advantage that it allows to control for observed and unobserved time invariant bilateral effects like geographical, historical, political and cultural influences as well as for time effects like cyclical influences, policy changes, decreases in transportation and communication costs, ..., which are common for all country pairs. Recent studies that estimate a three-way panel data model are Lewer and Van den Berg (2008), Pedersen et al. (2008), Ortega and Peri (2009), Mayda (2010), Beine et al. (2011b) for immigration to OECD countries or Gallardo-Sejas et al. (2006), Hooghe et al. (2008), Warin and Svaton (2008) for immigration to Europe, typically using a variant of the human capital model of migration with particular attention to economic determinants. In what follows, we present a brief overview of the research methodologies and empirical results obtained in these studies and highlight some of the methodological challenges they come across, which are further discussed in Section 1.4.

Karemera et al. (2000), Gallardo-Sejas et al. (2006) and Ortega and Peri (2009), for instance, use bilateral data to estimate a static extended gravity model that explains migration to the United States and Canada, to 13 European countries and to 14 OECD countries, for the year 2000, between 1976-1986 and between 1980-2005, respectively. After controlling for other potential determinants, all of them find support for the hypotheses that higher income countries attract more immigrants and that international migration decreases with distance. The authors, however, ignore the dynamic dimension of migration, i.e. they do not take into account the fact that previous migration has an influence on current migration through network effects and error correction.

Bertocchi and Strozzi (2008) and Mayda (2010), on the other hand, respectively investigate the role played by institutions and changes in the host countries' immigration policy and introduce dynamics into a utility maximization model by including lagged migrant flows as a proxy for networks. Yet, although Mayda (2010) uses a general method of moments (GMM) estimator when this variable enters the empirical specification, Bertocchi and Strozzi (2008) use pooled ordinary least squares, thereby completely ignoring unobserved heterogeneity and the dynamic panel bias stemming from its inclusion (see Section 1.4). For a dataset on nineteenth century migration, the latter find that besides economic and demographic differentials, also the quality of institutions matters. They do not find a significant effect for networks, though. Mayda (2010), on the other hand, concludes that migration rates to the OECD between 1980-1995 show considerable inertia (the coefficient on the lagged emigration rate is 0.66). Moreover, pull factors, particularly average income in the destination country, appear more important than push factors, an asymmetry that could be attributed to the demand side of the model, that is, the role played by host countries' migration policies.

Other studies of bilateral migration approximate network effects using migrant stocks instead of lagged migrant flows. Hooghe et al. (2008), Lewer and Van den Berg (2008), Pedersen et al. (2008) and Warin and Svaton (2008) all estimate a dynamic model for migration to Europe or the OECD at the end of the twentieth century. Hooghe et al. (2008) test the network approach by regressing unilateral migrant flows on migrant stocks at the beginning of the decade but find insignificant effects (even though the empirical specification includes no other controls besides a time trend and the size of the host country's population). Although the other three studies cover very similar country and time samples, they obtain fairly diverging results. Nonetheless, they all find positive significant effects for networks, irregardless of whether these are measured as the migrant stock before the sample period as in Lewer and Van den Berg (2008) or as the first lag as in Pedersen et al. (2008) and Warin and Svaton (2008). The impacts of the size of the population and the distance between origin and destination countries are in line with the predictions of the extended gravity models estimated in Lewer and Van den Berg (2008) and Pedersen et al. (2008). Also income per capita plays a significant role in both studies. Warin and Svaton (2008), however, find insignificant effects for distance and income per capita. Only with respect to unemployment in the destination country, the negative significant coefficient obtained by Warin and Svaton (2008) is similar to the one found by Pedersen et al. (2008). These discrepancies could be related to the fact that the three surveys use a different set of explanatory variables. Specifically, while Lewer and Van den Berg (2008) intend to demonstrate the usefulness of the gravity model to examine the determinants of both trade and migration, they add also indices quantifying how well destination and source countries adhere to the rule of law and protect property rights, respectively. Pedersen et al. (2008), on the other hand, control for the volume of bilateral trade and a number of sociopolitical characteristics while Warin and Svaton (2008) look into the relative importance of welfare state, geospatial and linguistic variables. Moreover, they use different estimation methodologies, varying from scaled ordinary least squares in Lewer and Van den Berg (2008) to fixed effects (FE) in Warin and Svaton (2008) and population averaged generalized estimating equations (GEE) in Pedersen et al. (2008). The latter argue that the lagged stock might be considered weakly exogenous given the significant variation in migration policies and asylum rules across countries and time. They do however recognize that the inclusion of migrant stocks might lead to biased and inconsistent least squares estimates. The model is estimated using a population averaged GEE estimator because of their skepticism about the adequacy of the GMM estimator in this framework. The latter is indeed not the best choice in the migration context, but the estimator they suggest requires a strong assumption about the error term (individual effects should not be correlated with the explanatory variables) for which the authors do not test.

Furthermore, four studies analyzing bilateral migration to Germany using the same approach can be compared to see to what extent their empirical results coincide. Specifically, Vogler and Rotte (2000) include the migrant stock at the beginning of the period and find a strong positive effect on African and Asian migration between 1981-1995. Their estimates also point out a strong positive impact of income disparities between home and abroad but suggest that improving living standards in the Third World results in an increase of migration flows to an industrialized country like Germany. Finally, also societal change, measured by the share of the urban population, as well as the political situation appear to have significantly shaped migratory streams to Germany during the sample period. The other three studies estimate some kind of error correction model based on the dynamic human capital model developed by Hatton (1995). Brücker and Siliverstovs (2006) perform a comparative analysis of 20 estimations methods using data on migration to Germany from 18 European countries in the period 1967-2001. As a proxy for net migration rates, the authors use the scaled change in migrant stocks between subsequent time periods (see also Beine et al., 2011a). Although the choice of an estimation procedure seems to have a substantial impact on the parameter estimates, the predictions of the model are very much in line with the hypotheses of the human capital model of migration, in particular with respect to the effects of the income per capita ratio and employment in the destination which appear positively significant in most estimations. Although the inclusion of lagged values of the migrant stock follows directly from the partial adjustment mechanism which is expected to govern migration, the authors acknowledge that network or herd effects cannot be ruled out from the positive impact of migrant stocks.

Alternatively, the empirical models estimated in Fertig (2001) and Boeri et al. (2002) allow for the rich migration dynamics present in Hatton's (1995) migration model. In fact, they both include changes and lagged levels of the human capital determinants (income and employment) and simultaneously estimate the impact of lagged migrant flows and stocks, taking into account also a number of institutional changes and regulations. Both analyzes cover more or less the same time period, i.e. 1960-1994 and 1967-1998, and consider immigration to Germany from 17 developed and 18 European countries, respectively. The dependent variable in Fertig (2001) is defined as the ratio of the annual change in net migration flows to the home population while Boeri et al. (2002) apply a similar ratio where net migration is replaced by migrant stocks. Nonetheless, whereas the results for the human capital determinants are consistent with theoretical predictions in both studies, they find opposite effects for the impact of the lagged dependent. The change in net migration is negatively significant in Fertig (2001), suggesting that migration to Germany varies around a stable level and will not be ever increasing in the future. In Boeri et al. (2002), on the other hand, lagged migration appears with a positive sign pointing to the existence of partial adjustment, though this finding is not discussed by the authors. Surprisingly, the results suggest a negative impact of lagged migrant stocks in both studies, indicating that they do not capture network effects but rather decreasing returns to migration, which Fertig (2001) links to harder competition on the labor market occurring when more immigrants from the same ethnic origin already live in the host country. Although both of these studies account for unobserved heterogeneity by estimating a model with fixed effects, neither of them convincingly corrects for the dynamic panel bias affecting this approach. Based on simulation studies, Boeri et al. (2002) argue that the coefficient for the lagged dependent variable is only moderately distorted in their data set and estimate their model using seemingly unrelated regression (SURE) techniques to account for correlation in the error terms caused by common shocks. Using the same reasoning, Fertig (2001), applies a maximum likelihood (ML) by iterated generalized least squares (GLS) procedure to account for group wise correlation due to unobserved common shocks, but equally fails to correct for the dynamic panel bias distorting the coefficient for the lagged dependent.

A last approach is different from the others in two aspects. First, it does not rely on migrant flow or stock data to capture the network effect but rather uses instruments to proxy for them. Second, it makes use of count data methods to account for the widespread presence of zero observations in bilateral migration data. As a matter of fact, Beine et al. (2011a) and Beine et al. (2011b) exploit the bilateral dataset on international migration by educational attainment to 30 OECD countries in 1990 and 2000, constructed by Docquier et al. (2009). Both studies explore how existing diasporas, defined as the stock of people born in a country and living in another one, affect the size and human-capital structure of bilateral migration flows. The authors define net migration as the difference between the migrant stocks observed in 1990 and 2000. Given the high proportion of zero observations, which is fully consistent with their utility maximization model, the authors use a two-step Heckman regression. Diplomatic representation of the destination country is believed to influence the probability of observing a diaspora between two countries without influencing the size of this diaspora, and can as such be used as an instrument in the probit equation. In order to address the presence of unobservable correlated effects (which cannot be controlled for directly given the cross-sectional nature of the data), the authors proceed to an instrumental variable estimation using (i) a dummy variable for temporary guest-worker agreements and (ii) a variable capturing the unobserved diaspora in the 1960s through a combination of the size of the population in the destination, the immigrant stock, the occurrence of armed conflicts in the origin and the distance between the origin and destination countries. Both surveys find evidence of a strong impact of existing diasporas. In fact, networks are the most important determinant of migration flows even after controlling for distance, colonial links and the presence of a common language. Furthermore, Beine et al. (2011a) disentangle the relative importance of the channels through which networks affect migration flows and Beine et al. (2011b) investigate the role of diasporas in defining the relative concentration of international migrants across education levels.

Although a discussion of the former results is beyond the scope of this introduction, a few observations considering the latter are worth mentioning. First of all, the changing nature of available data, for instance with respect to the level of aggregation or time span, has warranted different and innovatory approaches to modeling the determinants of migration. In fact, because of the improved availability and quality of migration data in the last ten years, one might question the validity of the findings in the older literature compared to those obtained in studies using more recent databases. Second, new data with educational breakdown show that the highly skilled are much more responsive to economic variables in general, and push factors in particular (e.g. poverty, bad institutions, etc.). On the contrary, they are less depending on networks. Relying on migration data broken down by education level, both McKenzie and Rapoport (2010) and Bertoli (2010) demonstrate how a decrease in migration costs generally has a stronger effect on low-skill versus high-skill migration to the United States from Mexico and Ecuador, respectively. Specifically, the latter show that negative selection of Ecuadorian migrants to the United States is largely explained by the size of the networks at destination. Building on the recent database developed by Docquier et al. (2009), also Beine et al. (2011b) provide similar evidence, showing that larger diasporas not only increase migration flows but also lower their average educational level, as expected. As argued by the authors, these findings suggest that diaspora effects leave little room for education-based selective policies in shaping the quantity and quality of migratory streams. Without a thorough reform of prevalent family reunification programs, existing migrant networks seriously constrain policies aiming at improving the educational quality or the ethnic diversity of migrants.

1.3.2 South-South migration

The driving forces behind migration to developing countries, especially South-South migration, on the other hand, remain poorly understood. Yet, as demonstrated in Section 1.1, the extent of migration in the South should definitely not be underestimated. The relatively little scholarly attention for South-South migration can primarily be linked to the lack of reliable data. Despite great improvements in the availability of international migration data during recent years, detailed long-term data on immigrant flows remain unavailable or incomplete for many developing countries. Keeping track of border crossings has simply not been a priority on the policy agenda in these countries. Because of the lack of data on international migration, most of the literature dealing with South-South migration has focused on rural-urban migratory movements within countries (see e.g. de Haan et al., 2002; Barrios et al., 2006; Quinn, 2006; Mullan et al., 2011) for migration within Mali, SSA countries in general, Mexico and China, respectively.

Two examples that use data covering multiple countries are worth mentioning. Barkley and McMillan (1994) estimated a migration decision model incorporating both economic conditions as well as political institutions, using panel World Bank data for 32 African countries during 1972-1987. They found support for their hypothesis that the presence of political freedom and civil liberties augments the responsiveness of labor migration to economic incentives. Alternatively, Barrios et al. (2006) analyzed the impact of environmental change on urbanization in SSA using a panel of 78 countries between 1960-1990. They confirmed that, contrary to the results for other developing regions, shortages in rainfall have acted to increase rural-urban movements in SSA countries.

Studies that analyze intraregional migration, on the other hand, mainly involve case studies such as mine migration to South-Africa (Lucas, 1985, 1987; Taylor, 1990), war-related border crossing between Zimbabwe and Mozambique (Hughes, 1999) or Mozambican refugee flows to Malawi (Koser, 1997) but also labor migration from Paraguay to Argentina (Parrado and Cerrutti, 2003) and political migration from Nicaragua to Costa Rica (Morales, 1997; Morales and Castro, 1999; Otterstrom, 2008). It is worth citing a few examples. Lucas (1987) examines what has driven the labor supply in the South African mines from the five most important origins: Botswana, Lesotho, Malawi, Mozambique and the South African homelands. A simultaneous econometric model of both the determinants of international migration to the South African mines and of some of the economic consequences for each of the labor supplying countries is estimated. For all the regions examined, the empirical results confirm that, when not constrained by immigration or emigration quotas, the number of miners is strongly related to the gap between wages (weighted by the probability of employment) available in the South African mines and at home. In their study of Paraguayan migration to Argentina, also Parrado and Cerrutti (2003) find a high responsiveness to fluctuations in macroeconomic conditions, particularly income differentials and peso over-valuation and a positive response to migrant networks and experience. In addition, their results suggest that Paraguayan migrants to Argentina tend to be positively selected with respect to educational attainment and skills.

The geographical scope and diversity of the South prevents the conduct of a complete analysis of migration between developing countries. As put forward by Bakewell (2009), there is not much sense in bringing together countries as diverse as Latvia and South Africa, or Mexico and Vietnam and one might also question the value of attempting to throw together their migration experiences under one rubric of South-South migration. Yet, focussing on specific geographical regions or groups of countries whose classification as developing does not depend on the definition being used, may still allow for a rigorous analysis of the determinants of South-South migration and as such add to an understanding of its driving forces. Given that it can unambiguously be classified as belonging to the South, SSA is an obvious candidate for this type of analysis, although also Asia might qualify. Yet, as far as we know, a comprehensive study of the determinants of intraregional migration within Asia, Latin America or Oceania (excluding Australia and New Zealand) has not yet been performed.

In fact, to our knowledge, the determinants of South-South migration have only been empirically investigated on a more comprehensive level for SSA countries. Specifically, Hatton and Williamson (2002) estimated the determinants of net out-migration rates (calculated as a residual from demographic accounting) in countries across SSA between 1977-1995. They found that Africans are especially driven by wage gaps and demographic booms in the sending country. However, even though the authors emphasize that the bulk of migration out of SSA countries is intraregional, they have no information about the migrants' origin or destination. As such, these results only offer an indication of the motivations for emigration out of developing countries, but not necessarily for South-South migration.

1.3.3 Immigrants' location choice

All of the above studies seek to analyze the relative importance of the driving forces behind international migration. To this day, little is however known about the location choice of immigrants within the destination country. The spatial concentration of immigrants in ethnic communities is nonetheless one of the most striking characteristics of international migration (Carrington et al., 1996; Chau, 1997; Winters et al., 2001; Heitmueller, 2003; Bauer et al., 2002, 2005). The most important explanation for this immigrant clustering is that spatial nearness enables the formation of social networks. By providing initial assistance to newcomers or help to face bureaucratic challenges in the destination country, social networks reduce some of the fixed initial costs that new immigrants come across. Although many surveys of international migration have shown that the existence of networks in the destination country positively affects the propensity to migrate (Massey and Denton, 1987; Stark and Taylor, 1989; Bauer and Zimmermann, 1997; Tsuda, 1999), only a limited number of studies empirically estimated the effect of social networks on the location of immigrants within the host country. To our knowledge, this analysis has been conducted only for the United States (see e.g. Bartel, 1989; Dunlevy, 1991; Zavodny, 1999; Bauer et al., 2002; Jaeger, 2007), for Australia (Chiswick et al., 2002), for France (Jayet and Ukrayinchuk, 2007), for Italy (Jayet et al., 2010) and for Switzerland (Ukrayinchuk and Jayet, 2011).

In his analysis of the location choice of post-1964 immigrants in the United States, Bartel (1989), for instance, finds that they are more geographically concentrated than natives of the same age and ethnicity and typically locate in cities with high concentrations of immigrants of similar ethnicity. Furthermore, the evidence suggests that the spatial concentration and the reliance on social networks is much lower for high skilled migrants. Also Dunlevy (1991), examining the settlement patterns of Caribbean and Latin immigrants in the United States, concludes that although social and economic forces vary across nationalities, network effects appear as a strong determinant for every nationality. Differentiating according to admission status, Zavodny (1999) and Jaeger (2007), both find that the presence of other foreign-born immigrants of the same ethnic origin is the primary determinant of immigrants' locational choice within the United States between 1989-1994 and 1971-2000, respectively, irregardless of the visa type. Although the former concludes that economic conditions, as measured by the unemployment rate and the average manufacturing wage, appear to play a minor role in most recent immigrants' settlement patterns, the latter observes a significant role of wage levels in all admission categories while employment-based immigrants are much more likely to locate in areas with low unemployment rates than other immigrants. Furthermore, using the Mexican Migration Project data, Bauer et al. (2002) examine the relative importance and interaction of social networks and herd effects in explaining the spatial clustering of Mexican immigrants in the United States. Their empirical results suggest that both network externalities and herds play a significant role in shaping the location pattern of immigrants. The significance and size of these effects however varies according to the legal status and skill level of the migrants. Similar to Bartel (1989), they find that skilled (and legal) migrants appear to be less dependent on network externalities than unskilled (and illegal) migrants. As far as concerns the herd effect, no significant difference is found between different types of migrants.

For the spatial concentration of immigrants in Australia, Chiswick et al. (2002) model variations in geographic concentration across birthplaces and regions using information on behavioral and socioeconomic characteristics of birthplace groups.

It is shown that the extent of geographic concentration of immigrant groups in Australia is negatively related to age at migration, duration of residence in Australia, and the percentage of the birthplace group that is fluent in English. Furthermore, there appear to be non-linear relationships between the extent of geographic concentration and both the availability of ethnic media and the distance between the country of origin and the place of residence in Australia.

Alternatively, Jayet and Ukrayinchuk (2007), Jayet et al. (2010) and Ukrayinchuk and Jayet (2011) investigate to what extent the settlement pattern of immigrants in France, Italy and Switzerland is driven by network effects or by traditional location factors, like the structure and behavior of the local labor market, housing market, public goods, and local tax rates. All of these surveys find evidence for very strong network effects in shaping the location pattern of immigrants in the respective countries. Specifically, this implies that a location may attract current immigrants mainly because it attracted previous immigrants, even if the traditional location factors are not a source of attractiveness. As far as concerns the Italian and the Helvetic cases, the main characteristics influencing the attractiveness of a location besides network externalities are its degree of urbanization and the state of the labor market. For the Helvetic case, also rental-housing supply and tourist attractiveness seem to matter whereas the role of unemployment appears irrelevant in determining the immigrant's location choice. In the Italian case, however, especially socioeconomic location factors are important and networks play only a significant role for some nationalities such as Romanians, Poles and Ukrainians. Furthermore, immigrants tend to prefer more dense provinces where unemployment rates are lower and which are located closer to the country of origin. In the French case, finally, the econometric analysis shows that persistence is not only due to the presence of network externalities but is also due to the existence of time invariant location factors. Similar to the Italian case, it is shown that immigrants

are also attracted by areas where there are low unemployment levels, increasing levels of employment opportunities, a large private rented housing sector, a mild climate and public amenities.
Despite the importance of many other European countries as destinations for immigrants, an analysis of their spatial repartition has not yet been performed, mainly because the required data is not available.

1.4 Methodological challenges

In the previous sections, it has been shown that, although some of the recent migratory streams can be related to regional wars, political conflicts and natural disasters, they are predominantly driven by economic motivations such as prevailing income disparities or job opportunities as well as network externalities. The latter motivations also show up as important factors shaping the geographical spread of immigrants in the destination country. Yet, the relative importance of these migration and location determinants differs across sample periods and country sets. Furthermore, also the choice of an empirical method has been shown to affect empirical outcomes. Specifically, recent immigration studies come across a number of methodological challenges that might seriously influence empirical results depending on the way they are addressed. An overview of the most important methodological challenges and how they have been tackled in the literature is presented below.

1.4.1 Dynamics in the migration decision

As became clear in Section 1.3, network effects, proxied by including either the lagged migrant flow or the stock of migrants in the destination country, are usually found to be very important in determining international migration flows and location patterns. The coefficients on these dynamic factors are typically positive and statistically highly significant.

In fact, the first dynamic empirical studies of international migration, typically proxying for network effects using lagged migrant flows, found it to be the most significant variable in the regression (Gould, 1979). As outlined above, also more recent studies, such as Bertocchi and Strozzi (2008) and Mayda (2010), account for dynamics in the migration equation by adding lagged migrant flows to capture the family-friends effect. As opposed to early studies of international migration, the latter rely on bilateral panel data on migrant flows, which typically hold a small number of time series observations on a moderate number of cross-sections. Estimating a dynamic model using such data is particularly challenging. The main problem is that the lagged dependent variable is by construction correlated with the individual effects. This renders the pooled ordinary least-squares (POLS) estimator, as used by Bertocchi and Strozzi (2008), biased and inconsistent. A within transformation wipes out the individual effects by taking deviations from individual sample means, but the resulting fixed effects estimator is biased and inconsistent for fixed T and N going to infinity (see Nickell, 1981). Given this inconsistency, the dynamic panel literature focuses mainly on a first-difference transformation to eliminate the individual effects while handling the remaining correlation with the (transformed) error term using instrumental variables (IV) and GMM estimators (see e.g. Mayda, 2010). Unfortunately, these GMM estimators are known to suffer from a weak instruments problem (see e.g. Bun and Windmeijer, 2010), which implies a small sample bias, large uncertainty around coefficient estimates and strong sensitivity to instruments choice. Alternatives to this approach are discussed in Chapter 2.

Nonetheless, as emphasized by (Dunlevy and Gemery, 1977), the network effect is better captured by the stock of all previous migrants, as opposed to those who migrated only in the previous year. (Greenwood, 1969; Vedder and Gallaway, 1972; Levy and Wadycki, 1973) replaced the lagged dependent by the migrant stock and found positive and highly significant coefficients. As mentioned above, also more recent studies such as Hooghe et al. (2008), Lewer and Van den Berg (2008), Pedersen et al. (2008), Warin and Svaton (2008) and Vogler and Rotte (2000) follow this approach and predominantly find evidence for strong positive network effects.

It can however be argued that the migrant stock is the sum of all past migration flows less deaths and return migration, and that, consequently, it is itself a function of all those factors that influenced the earlier migration flows (see Nelson, 1959; Greenwood, 1969; Laber, 1972). Therefore it will be correlated with all the explanatory variables and affect their parameter estimates. However, multicollinearity is no reason to omit the migrant stock variable as this may result in a specification bias as well as in a loss of information regarding the network effect. The interlinkage between migrant flows and stocks, however, forms another source of endogeneity which acquires an appropriate estimation method. As mentioned above, the fixed effects estimator, used by e.g. Vogler and Rotte (2000), Hooghe et al. (2008) and Warin and Svaton (2008), is biased and inconsistent in the context of bilateral migration flows and stocks. Yet, the authors approximate the social network using lagged values of the migrant stock (at the beginning of the period or decade) and the first lag, respectively, in order to avoid endogeneity issues. The same procedure is followed in Lewer and Van den Berg (2008) and Pedersen et al. (2008), who turn to scaled OLS and a population averaged GEE procedure, respectively. Only the latter method is able to convincingly account for the dynamic panel bias but it requires that individual effects are uncorrelated with the explanatory variables, a strong assumption for which the authors do not test. Beine et al. (2011a) and Beine et al. (2011b), on the other hand, adopt an

IV approach through the use of a dummy variable for temporary guest-worker agreements and a variable capturing the unobserved diaspora in the 1960s as instruments for the migrant stock.

A final point to raise concerns a longstanding discussion, dating back to e.g. Laber (1972) and Dunlevy and Gemery (1977), on whether these dynamic terms represent network effects or rather capture a partial adjustment mechanism reflecting sluggishness in the response of migration to shifts in its underlying determinants. The latter interpretation suggests a negative sign for the coefficient on the migrant stock to prevent migrant flows from being ever increasing in the future. This implies that migrant flows become smaller as we get closer to the equilibrium stock of migrants in the destination country. As such, network effects and the adjustment process cannot be separately identified from the parameter of migrant stocks. Yet, in an attempt to disentangle the network effect from the partial adjustment mechanism, Dunlevy and Gemery (1977) argue that lagged migrant flows and migrant stocks should both be included as determinants. Only then it is possible to separately identify these two effects. If both are present, it is not possible to quantify the size of partial adjustment and network effects as their coefficients are a combination of both effects. Yet, even though nothing can be said about the size of these effects, it can be determined wether they are significantly different from zero. In Dunlevy and Gemery (1977) both appear significantly positive in the same regression, suggesting that two separate mechanisms are at work. This is not true in Fertig (2001) and Boeri et al. (2002) who find a negative impact of lagged migrant stocks, suggesting that they do not capture the network effects but rather decreasing returns to migration. Also the lagged migrant flow is found to be negatively significant in Fertig (2001), which is explained by the authors as an indication for German migration fluctuating around a stable level and as such preventing it from being ever increasing in the future. The positive impact of lagged migrant flows in Boeri et al. (2002) is not discussed by the authors. Nonetheless, using a FE estimator and ML by iterated GLS, neither of these studies convincingly correct for the dynamic panel bias distorting the coefficient for the dynamic variables.

1.4.2 Zero migrant flows

A complication that often arises when using bilateral migration flows, concerns the presence of zero magnitude flows between origin-destination pairs. This is true for immigration between countries or from one country to a specific region within a destination country and thus applies for both the analysis of the determinants of migration and the evaluation of the location pattern of immigrants within the destination country. Many countries or local governments do not report a single migrant from a specific origin country resulting in a zero bilateral flow. As illustrated in (Beine et al., 2011a), a large number of zero values might be the result of a statistical truncation process. In some countries, national statistical agencies do not report some low number of immigrants from a specific origin country in order to preserve statistical confidentiality. Similarly, due to imperfect sampling, many smaller migrant flows and stocks are likely not fully captured in census and labor force surveys used to compile bilateral migration databases. Nonetheless, the majority of zero values reflects true zeros that can be associated with negative utility arising from a move between these locations (LeSage and Pace, 2009). As such, the absence of migration flows between origin-destination pairs signals that the costs of migration between locations outweigh its prospective benefits, so that potential migrants simply do not migrate. Ignoring such zero values thus introduces measurement error and obstructs any evaluation of the determinants of international migration or location choice. The presence of a large number of zero flows might however also result in inconsistent parameter estimates. Especially when the empirical model is estimated using the ML estimator, it might be argued that a large number of zero flows invalidates the normality assumption that is required.

One suggestion to address the issue of zero flows is to aggregate the data to larger spatial units or to cumulate flows over a longer time period. This however only avoids the problem rather than actually dealing with it and is not really helpful when the specified level of aggregation is the appropriate one. An alternative approach uses count data methods such as multinomial logit or Poisson models. Beine et al. (2011a) and Beine et al. (2011b), for instance, compare the results obtained with different estimation techniques and analyze the quantitative robustness of network effects on migration flows to the choice of a particular method. Because a log specification removes zero observations from the sample, OLS estimates are likely to be inconsistent in the presence of a high occurrence of zeros. In order to minimize the bias due to selection issues, two variants of the Heckman two-stage method are used, depending on when an instrument in the probit equation is used. Alternatively, the authors proceed to an IV approach using two instruments, i.e. variables uncorrelated with migrant flows but strongly correlated with migrant stocks, which allows them to address the presence of unobservable correlated effects. Like OLS, however, the IV approach is subject to issues related to selection bias. Finally, a Poisson pseudo-maximum likelihood estimator is used to deal with zero observations in the migration data, as suggested by Santos Silva and Tenreyro (2006) who demonstrated that the use of log linearization in gravity models leads to inconsistent estimates of the coefficients resulting in overestimated coefficients for, for instance, colonial ties, geographical proximity, and bilateral trade agreements. Nonetheless, especially for the impact of diasporas, the coefficient estimates from the cross-sectional specification are remarkably robust across the five estimation methods.

The occurrence of zero migrant flows might even be more prevalent in bilateral data at the local level. The use of count data methods to account for the large number of zero flows is therefore more common in an examination of the location pattern of immigrants within a certain destination. In their analysis of the spatial repartition of immigrants in the United States, Bartel (1989), for instance, estimate a multinomial logit model consistent with random utility maximization. The same approach is followed in Jayet et al. (2010) and Ukrayinchuk and Jayet (2011) for immigrants in Italy and Switzerland, respectively. For France, on the other hand, Jayet and Ukrayinchuk (2007) argue that their data suffer from overdispersion and turn to a negative binomial approach.
It needs to be said that the application of count data methods requires the elimination of non-negative values which are perfectly reasonable in a database of bilateral migration. Negative flows can occur, for instance, when return migration exceeds immigration between two countries. Although in this case, it is impossible to estimate a double-log empirical specification, there is no reason why this model could not be estimated using standard estimation techniques. To account for the non-normality of the migrant flow, one can for instance use a quasi-maximum likelihood estimator (QMLE), which produces consistent estimates, even if the likelihood function is not entirely correct (see White, 1982; Verbeek, 2012). The small sample distribution of the QMLE can then be obtained in a numerical way by resampling the original data and constructing a simulated distribution of the QMLE which allows for the calculation of robust standard errors.

1.4.3 Spatially dependent migration

All of the existing theoretical models of international migration assume independence of observations, an assumption that might be problematic in several contexts. Migratory streams between any pair of locations are likely to depend not only on the relative attractiveness of these locations, but also on the characteristics of alternative destinations. In general, the weight attributed to the characteristics of other potential destinations is believed to decrease with distance. The migration literature points out distance as one of the major deterrents to migration (Greenwood, 1975; Cushing and Poot, 2004). Yet, as argued by Curry (1972), Griffith (2007) and LeSage and Pace (2009), the inclusion of distance as an explanatory variable, as is usually done in gravity models, does not effectively capture spatial dependence in origin-destination flows.

Nonetheless, despite the widespread recognition of the need to account for spatial dependence in analyzing human migration (Cushing and Poot, 2004; LeSage and Pace, 2008, 2009; Mitze, 2009), attention for spatial interaction in the migration literature remains scarce. Although her theoretical model suggests that the decision to migrate involves only a country of origin and one particular destination, Mayda (2010) investigates to what extent potential migrants consider also mean income opportunities in other potential host countries. Inspired by the multilateral trade resistance term introduced in Anderson and van Wincoop (2003), this approach puts the migration decision in a multi-country framework.[2] Mayda (2010) includes a weighted average of income per capita in the other destination countries as a control for their time-varying attractiveness and finds that third-country effects have a negative impact on bilateral migration flows, as expected.

Alternatively, Ortega and Peri (2009) develop a nested logit model consistent with random utility maximization in which they fully control for any factor depending on country of origin and year through the inclusion of origin-time effects. In the

[2] The approach is also related to the new economic geography literature in which Blonigen et al. (2007), for instance, provide an explicit theoretical basis for the presence of spatial dependence in foreign direct investment streams. They argue that the latter are not only affected by the local market potential but also by the country's export potential, suggesting that not only the country's own average income but also that of neighboring countries should be considered. A similar reasoning could be followed to explain the interest of potential migrants in the average income of neighboring countries besides that of the destination itself.

nested logit model, the latter capture - among other things - the size of the migrant flow, which provides a correction for the average unobserved heterogeneity between migrants and non-migrants. An important implication of this approach is that, unlike in the case of a multinomial logit model, an increase in the attractiveness of one destination does not necessarily draw proportionally from all other destinations. Rather, bilateral migration between two countries might drop following an increase in the attractiveness of an alternative destination. The sorting of immigrants across locations however still ignores a change in the attractiveness of a third destination in the choice set (Bertoli and Fernández-Huertas Moraga, 2012).

A more general approach is followed by Bertoli and Fernández-Huertas Moraga (2012), who propose the use of the common correlated effects estimator developed by Pesaran (2006), to control for the influence exerted by other destinations on bilateral migrant flows. Following the trade literature, the authors identify this influence as “multilateral resistance to migration". Building on a random utility maximization model, the authors show that multilateral resistance to migration leads to biased estimates whenever the assumption of independence of irrelevant alternatives (IIA) fails. The reverse also holds: whenever the IIA property holds, the time-varying attractiveness of alternative destinations in the choice set can safely be disregarded. Using data on the Spanish immigration boom between 1997 and 2009, they find a smaller effect of average income per capita and a larger effect of migration policies compared to those obtained from estimation methods that ignore this interconnectedness.

Another way to account for the presence of spatial dependence in the migratory process concerns the use of spatial econometric techniques. Yet, despite rapid developments in this literature, spatial econometrics has not yet found much application in empirical research on the determinants of international migration.

The empirical literature on location decisions, on the other hand, often explicitly acknowledges the presence of this spatial dependence and makes use of spatial econometrics techniques. In the migration context, however, only Jayet et al. (2010) and Ukrayinchuk and Jayet (2011) explicitly address spatial dependence in the location of immigrants in the destination country. Given the strong spatial concentration of immigrants in many destination countries, the error terms can be expected to exhibit spatial dependence. Both studies use a two-step procedure in which (i) the network effect and fixed effects are estimated using ML and (ii) the fixed effects are regressed on the observable location factors to obtain an estimate of their impact on the attractiveness of Italian provinces. The second stage is estimated using either OLS or ML depending on whether spatial autocorrelation is accounted for. The authors find, at least in some cases, a highly significant coefficient for the spatial error term suggesting a great deal of spatial interconnection between the location of immigrants in Italian provinces and Swiss regions.

An important advantage of spatial regression techniques is that they do not only correct for shocks that are spatially correlated across locations, as is the case for the common correlated effects estimator, but they also allow to identify the spatial effects and the source of the spatial correlation. Moreover, they do not only provide an answer to the type of spatial interaction described above, but are also able to address other forms of spatial dependence justified by both theoretic and econometric motivations. An example of the former concerns migration regulations, which are difficult to measure in practice because of their qualitative nature and, therefore, often omitted in empirical specifications. They form, however, another important barrier to migration and are likely to be correlated across countries. Governments might, for instance, decide to set in place certain policy measures after having observed those set by neighboring countries. This type of spatial interdependence might be explicitly integrated in the formal specification of the theoretical model or it might be motivated from an econometric perspective by looking upon bilateral flows as describing a diffusion process over space with a time lag. This form of spatial dependence typically shows up in cross-sectional models with a spatial lag of the dependent variable. Another important econometric motivation for the use of spatial regressions concerns the presence of omitted latent influences that are spatial in nature, typically leading to a spatial Durbin model (SDM) with spatial lags of both the dependent and explanatory variables (LeSage and Pace, 2009). Again, migration policy appears an obvious candidate given that it is often an omitted latent influence that is both correlated with the explanatory variables and across locations.

LeSage and Pace (2008, 2009) show that the SDM is less affected by omitted variable bias than a model that ignores spatial dependence. This holds when the omitted variable is truly involved in the data generating process, but also when it is not, its inclusion does not lead to bias in the estimates. Consequently, the authors suggest relying on a model that includes spatial lags of the dependent and explanatory variables even if this seems counter to the underlying theory behind the model.

In a model of bilateral flows (like international trade or migration), the spatial interaction structure is likely to be more complex compared to standard spatial lag or spatial error models, because it needs to take into account spatial correlation of the flows at both origins and destinations (LeSage and Pace, 2008, 2009). Consequently, the latter suggest to control for three potential sources of spatial dependence that may arise between bilateral flows: origin, destination and destination-to-origin based dependence.

An implication of accounting for spatial dependence is that the estimated parameters cannot be interpreted as usual in a standard linear regression model. Cross-country interactions prevent the parameter estimates from being interpreted as the simple partial derivatives of the dependent variable with respect to the explanatory variables (see Anselin and Le Gallo, 2006; Kelejian et al., 2006; LeSage and Pace, 2009). Pace and LeSage (2006) and LeSage and Pace (2009) suggest three summary measures of the varying impacts of changes in an explanatory variable across countries: the average direct impact (the impact from changes in the ith observation of variable k on country i, averaged over all countries), the average indirect impact (the effect of changes in the ith observation of variable k on country j ($\neq i$), averaged over all countries, capturing the spillover effects of a change in country i on all other countries) and the average total impact (the sum of the previous two, reflecting how changes in a single country potentially influence all observations). The direct effects correspond the most to the typical regression coefficient interpretation that represents the average response of the dependent variable to independent variables over the sample of observations. As such, they allow for an explicit comparison with parameter estimates from other studies on migration determinants in the literature. The main difference is that the direct effect takes into account feedback effects from changes in country i to country j and back to country i itself.

1.4.4 A combined approach

Ideally, an empirical evaluation of the driving forces behind international migration would tackle each of the three methodological issues described above simultaneously. To this day, unfortunately, a combined approach to face these challenges has not yet been developed. The existing literature typically tries to address one issue (such as Pedersen et al., 2008 and Mayda, 2010 for dynamic panel bias or Bartel, 1989 and Jayet and Ukrayinchuk, 2007 for zero flows) or at most two issues at the same time, i.e. a combined approach for dynamic panel bias and zero flows (see e.g. Beine et al., 2011a,b) or for zero flows and spatial dependence (see e.g. Jayet et al., 2010; Ukrayinchuk and Jayet, 2011).

One of the more recent attempts to tackle both the high occurrence of zero values and spatial dependence in bilateral flows, concerns the multinomial spatial probit approach developed by LeSage and Pace (2009). In line with location choice theories, this procedure is based on a random utility framework. Stacking utility differences across observations in the choice set results in a system of seemingly unrelated SAR or SDM equations, depending on whether spatial lags for the explanatory variables enter the specification. Conditioning on the latent values of the dependent variable by treating them as parameters in the model, these models can be estimated using Markov Chain Monte Carlo (MCMC) techniques. The latter decomposes the posterior distribution into a set of conditional distributions for each parameter in the model. Bayesian parameter estimates are then obtained from repeated sample draws from these conditionals. This approach has the advantage that it decomposes a complicated estimation problem into simpler problems without having to carry out numerical integration of the posterior distribution with respect to the parameters as was needed in conventional Baysian methodology. It is however still considered quite controversial given the subjective choice of prior distributions, the lack of an objective principle for choosing a non-informative prior and the potential influence of these choices on the estimation outcome. Moreover, MCMC techniques cannot guarantee that convergence has taken place. Finally, as put forward by LeSage and Pace (2009), though this approach might seem a relatively straightforward extension of the SAR probit model, it might be very slow and a number of computational issues limit its usage in practical applications.

In conclusion, despite great improvements in the migration literature, an all inclusive approach seems unrealistic at this moment, so that the best we can do is simultaneously deal with two out of the three methodological challenges described above. An overview of how this has been put into practice in each of the following chapters can be found in Section 1.5.

1.5 Outline, contributions and results

In Chapter 2 of this dissertation, we reconsider the determinants of South-North migration and contribute to the literature by addressing the first methodological challenge described in Section 1.4. Specifically, we investigate the determinants of bilateral immigration to the OECD from both advanced and developing origin countries between 1998 and 2007 using the OECD's International Migration Database. Our contribution is twofold. First, we estimate a dynamic model of migration using a three-way panel data model. This framework allows to control for observed and unobserved time invariant bilateral effects like geographical, historical, political and cultural influences as well as for time effects like cyclical influences, policy changes, decreases in transportation and communication costs, ..., which are common for all country pairs and reduce the risk of biased results. In contrast to the literature and in line with Hatton (1995) we include both lagged migration and the migrant stock, which allows us to separately identify network effects and dynamics stemming from partial adjustment. Second, we estimate this dynamic panel data model using an extended version of the bias-corrected fixed effects (BCFE) estimator suggested by Everaert and Pozzi (2007). This estimator corrects for the dynamic panel data bias of the fixed effects estimator using an iterative bootstrap algorithm. Its main advantage over GMM estimators for dynamic panel data is that it combines a small bias with a relatively small standard error. We slightly adjust the bootstrap algorithm of the BCFE estimator to take into account that in our model the dynamic panel data bias is induced by the lagged migrant flow as well as by the migrant stock. Using Monte Carlo experiments, we demonstrate that this adjusted BCFE estimator performs well in the specific context of our model and is preferable to alternative estimators.

Our results indicate that immigrants are primarily attracted by better income opportunities abroad and much less by income at home and by employment rates both at home and abroad. High public services are found to discourage migration from advanced countries but exert a pull on migration from developing sources, confirming the welfare magnet hypothesis. Furthermore, we find evidence of strong dynamic effects. Both the lagged migration flow and the migrant stock have a strong positive and significant impact on current migration, the former indicating dynamic effects stemming from the process by which expectations about future earnings are formed and updated while the latter indicates network effects. Further evidence that dynamics play a prominent role in the migration model arises from the observation that misspecifying the model by omitting the lagged migration flow or the migrant stock and/or not correcting for the dynamic panel bias has a strong impact on the estimation results. Therefore, care should be taken when specifying the dynamic structure of the model and selecting the estimation method.

Although the determinants of migration in a South-North context have already been well-studied in the empirical literature, Chapter 2 contributes to the literature by using three-way panel data on migration flows and stocks to provide an answer to one of the major methodological challenges that arise in the estimation of dynamic panel models of international migration. The determinants of South-South migration, on the other hand, have not been studied as thoroughly as those of South-North migration and remain as such poorly understood. In an attempt to fill this gap, Chapter 3 examines what has been driving intraregional migration in SSA, with particular attention for the second and third methodological challenges outlined above.

The recently constructed Global Bilateral Migration Database (GBMD) described in Özden et al. (2011) allows us to exploit bilateral panel data to investigate incentives for South-South migration as is usually done in a South-North context. Spanning the period 1960-2000, it is the most comprehensive and consistent database on bilateral South-South migration available at present. The database provides statistics on migrant stocks for each decade during this period. The change in migrant stocks between subsequent time periods can then be used as a measure of net migration flows (see also Beine et al., 2011; Marchiori et al., 2012). This approximation is not perfect as it does not take into account deaths and return migration during the 10 years between observation points. Yet, following Beine et al. (2011b), we believe that it is accurate enough to provide a reasonable approximation for net migration.

As such, the first contribution of Chapter 3 concerns the use of bilateral panel data to evaluate the factors affecting migration between SSA countries. Our theoretical framework is based on Sjaastad's (1962) human capital model of migration and encompasses economic variables as well as network effects, geographical and cultural proximity, demographics, the socio-political landscape and the environmental impact. This comprehensive model allows us to evaluate the relative importance of the different factors driving migration patterns in SSA. The model is estimated using data from the GBMD, for 42 origin and destination countries between 1980-1990 and 1990-2000. The second contribution of Chapter 3 relates to our estimation approach, which takes into account potential spatial interaction between origin-destination flows. In the context of this chapter, the omitted variable motivation described above appears particularly relevant. We do not a priori impose any spatial dependence in the migrant flow, as this does not immediately follow from current theoretical models motivated by utility considerations. In line with LeSage and Pace (2008, 2009), our starting point is consistent with the human capital model, which posits a non-spatial theoretical relationship underlying migration flows. Specifically, we follow the approach of LeSage and Pace (2008, 2009) outlined above, which starts from a spatial Durbin model, the most general model of spatial dependence, and relies on specification tests to determine which model best describes the data. Given the relatively large number of zero migration flows between the SSA countries in our sample, we use a QMLE to account for the non-normality of the migrant flow.

Our evidence suggests that SSA migration results from a multidimensional set of factors. The results seem to confirm the hypothesis of Ratha and Shaw (2007) that South-South migration is to a large extent driven by income differences, networks and geographical proximity. On the other hand, we also find support for the role played by conflicts in the home country and relative freedom in the host country. Furthermore, deteriorating environmental conditions in a specific country discourage migration towards it. While for the economic determinants and migrant networks, the direct effects seem to dominate, our results suggest the presence of spillover effects (and hence a regional dimension) for the socio-political and environmental determinants. As such, our results are in line with the main findings of the descriptive literature on South-South migration determinants, as discussed for instance in Bakewell (2009), for which we provide econometrically based evidence. Caution in generalizing these results to other contexts of South-South migration remains necessary, as the South combines a largely heterogeneous mixture of countries with idiosyncratic profiles and region specific developments. Yet, it should be clear that an analysis of migration in a South-South context should include economic determinants as well as other determinants that match the specificities of the particular setting.

Chapter 4, finally, analyzes migratory streams to Belgian municipalities between 1990-2007. Despite the renewed attention for the determinants of migration in the literature of the last two decades, the dynamics in the spatial repartition of immigrants within a destination country remain poorly understood. Nonetheless, the location pattern of immigrants is conditioned by the distribution of natives (Le Bras and Labbé, 1993; Chiswick and Miller, 2004), but usually follows different dynamics that may exhibit a strong impact on the welfare of both natives and immigrants, on the spatial distribution of natives (Borjas, 1993; Winkelman and Zimmerman, 1993; Friedberg and Hunt, 1995; Borjas, 2003) and also on the negative perception of immigrants to natives (Roux, 2004).

Whereas Chapters 2 and 3 as well as many other surveys of international migration have shown that the existence of networks in the destination country has a positive effect on the propensity to migrate (Massey and Denton, 1987; Stark and Taylor, 1989; Bauer and Zimmermann, 1997; Tsuda, 1999), only a limited number of studies empirically estimated the effect of social networks on the location of immigrants within the host country. The lack of research can mainly be attributed to the absence of the required data for many countries of destination. The Belgian population register, however, constitutes a rich and unique database of yearly migrant inflows and stocks with a detailed breakdown by nationality and age cohort, which allows us to distinguish the immigrants of working age (age 20 to 64). More specifically, the Belgian population register provides information on the number of immigrants arriving and living in each of the 588 municipalities between 1990 and 2007, covering 97 nationalities. It keeps track of every foreigner who resides in Belgium for more than 3 months. Whereas legal immigrants are enrolled in the register of the municipality where they reside, illegal migrants do not appear in the immigration statistics as long as their situation has not been regularized. Neither do asylum seekers, who are, as of 1995, enrolled in a special waiting register until they have been granted refugee status. As such, this database offers a unique opportunity to study the location pattern of immigrants using detailed bilateral flow and stock data at Belgian municipality level.

Besides providing insight into the spatial distribution of immigrants in Belgium through a descriptive analysis based on these data, Chapter 4 contributes to the migration literature in two important ways. On the one hand, we develop a hierarchical (nested logit) model of the location choice of immigrants that is consistent with random utility maximization and robust to the presence of a large number of zero flows. Specifically, we expect labor and housing market variables to operate on a different level such that immigrants first select a region roughly corresponding to a labor market, and subsequently choose the municipality within this region that maximizes their utility. Our evidence suggests that this is a valid assumption and that immigrants' behavior is consistent with random utility maximization for all nationalities. On the other hand, we investigate the relative importance of social networks versus these labor and housing market variables as well as other location specific characteristics such as the presence of public amenities, touristic attractiveness or distance to the nearest border. Although existing social networks usually act as a significant pull towards newcomers, both in the municipality itself and in those surrounding it, we find that the spatial repartition of Belgian immigrants is predominantly driven by location-specific characteristics such as housing and labor market variables.

A decomposition of predicted immigration rates reveals that the predictive power of our nested logit model is fairly high. We find that the genuine attractiveness of municipalities typically dominates the positive influence of social networks.

Finally, we estimate the parameters of the time invariant location determinants in our empirical model. We do not a priori assume a specific structure for spatial dependence in the local effects, but rely on a series of LM tests to select the most appropriate specification. The test results reveal that the model should include spatial lags for both the dependent and the explanatory variables. As such, the relative importance of the location characteristics are investigated using a SDM framework. The determinants of local effects vary by nationality, as expected, but with some noticeable parallels. The distance to the nearest border, for instance, is a significant determinant for immigrants from neighboring countries, as we would expect from the strong concentration of Dutch, French and German immigrants along the border of their origin country. But also the presence of public amenities and the municipality's touristic attractiveness act as a strong pull for immigrants. In sum, Chapter 4 addresses both the second and third methodological challenges and shows that the location choice of immigrants in Belgium is primarily determined by housing and labor market variables which vary in time, but also the genuine appeal of municipalities captured by the presence of public amenities and its touristic allure plays an important role in shaping the spatial repartition of immigrants.

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2

Determinants and Dynamics of Migration to OECD Countries in a Three-Dimensional Panel Framework[1]

[1]This chapter is the result of joint work with Prof. dr. Gerdie Everaert and Prof. dr. Glenn Rayp.

Abstract

This chapter investigates the determinants of bilateral immigrant flows to 19 OECD countries between 1998 and 2007 from both advanced and developing origin countries. We pay particular attention to dynamics by including both the lagged migrant flow and the migrant stock to capture partial adjustment and network effects. To correct for the dynamic panel data bias of the fixed effects estimator we use a bootstrap algorithm. Our results indicate that immigrants are primarily attracted by better income opportunities, higher growth rates and short-run increases in the host country's employment rate. High public services discourage migration from advanced countries but exert a pull on migration from developing sources, in line with the welfare state hypothesis. Furthermore, we find that both partial adjustment and network effects should be considered crucial elements of the migration model and that a correction for their joint inclusion is required.

JEL Classification: F22, J61, C33

Keywords: International migration, Network effects, Dynamic panel data model, Bias correction

2.1 Introduction

Recent changes in both the size and the composition of migrant flows to OECD countries have placed international migration high on the policy agenda in many countries. In terms of size, the number of immigrants residing in the 33 current OECD member states roughly increased from about 42 million in 1980 to over 87 million in 2000. In terms of composition, the expansion of immigration from Central and Eastern Europe to Western Europe following the enlargement of the European Union is apparent, but also migration from India and China to non-European countries has been growing at a steady pace. Understanding the forces that drive such migration patterns is important for the conduct of migration policy. A general theoretical view on the determinants of migration is the traditional push-pull model (see e.g. Lee, 1966; Todaro, 1969; Borjas, 1989) in which costs and benefits of migrating are determined by push factors of conditions at the origin and pull factors of prospects at the destination. Migration occurs when the net present expected value of migrating is positive. Typical factors are wages and (un)employment rates in both the origin and the destination country, which together determine the expected wage differential. Other factors are levels of social expenditures (Borjas, 1987, 1999; Pedersen et al., 2008; Warin and Svaton, 2008), geographical and cultural proximity (Karemera et al., 2000; Brücker and Siliverstovs, 2006; Lewer and Van den Berg, 2008; Pedersen et al., 2008; Warin and Svaton, 2008; Mayda, 2010) but also differences in living standards and the sociopolitical environment (Karemera et al., 2000; Vogler and Rotte, 2000; Bertocchi and Strozzi, 2008; Hooghe et al., 2008). A popular dynamic factor is given by network effects, which suggests that having friends and family from the same origin living in the host country lowers the monetary and psychological costs of migrating and thus increases migration to that country. As such, migration may become a self-perpetuating process. Surveying empirical findings (see Gould, 1979; Bauer and Zimmermann, 1999, for excellent surveys of the earlier results), the main reason for migration appears to be the search for better economic conditions. Nearly all studies find a significant effect of income differentials between the origin and destination country. The findings regarding (un)employment rates in both sending and receiving countries are more ambiguous, though. Network effects, proxied by including either the lagged migrant flow or the stock of migrants in the destination country, are also found to be very important. The coefficients on these dynamic factors are typically positive and statistically highly significant. Moreover, when excluding such dynamic factors, regression errors are often found to exhibit severe serial correlation. However, there is a longstanding discussion, dating back to e.g. Laber (1972) and Dunlevy and Gemery (1977), on whether these findings signal strong network effects or rather a partial adjustment mechanism reflecting sluggishness in the response of migration to shifts in its underlying determinants. Building on microeconomic utility maximization, Hatton (1995) derives a formal dynamic model of migration in which both the lagged migration flow and the stock of migrants enter as separate determinants, with the former capturing dynamics resulting from uncertainty about future relative income streams and the latter capturing network effects.

Although the empirical literature on migration determinants has made tremendous progress in recent years, it is still plagued by a number of flaws. First, due to data limitations, most studies have estimated the determinants of international migration to a single destination country, either ignoring the origin of migrants, i.e. pure time series models with time as the only dimension (see e.g. Hatton, 1995) or accounting for the origin of migrants using a two-dimensional panel data model with bilateral effects (see Karemera et al., 2000 for immigration to Canada and the US or Vogler and Rotte, 2000; Fertig, 2001; Boeri et al., 2002; Brücker and Siliverstovs, 2006 for the German case). The recent availability of comprehensive data on bilateral migration offers a three-way panel dataset which allows for the inclusion of time dummies next to bilateral effects. This has the important advantage that it allows to control for observed and unobserved time invariant bilateral effects like geographical, historical, political and cultural influences as well as for time effects like cyclical influences, policy changes, decreases in transportation and communication costs, ..., which are common for all country pairs. Recent studies that estimate a three-way panel data model are Lewer and Van den Berg (2008), Pedersen et al. (2008), Mayda (2010) for immigration to OECD countries or Gallardo-Sejas et al. (2006), Hooghe et al. (2008), Warin and Svaton (2008) for immigration to Europe. Second, none of the above mentioned studies (except Fertig, 2001) allow for the rich migration dynamics present in Hatton's (1995) model, i.e. some studies use a purely static empirical specification while dynamic specifications include either the lagged migrant flow or the stock of migrants but never both of them together, which is required to capture both partial adjustment and network effects. Third, panel datasets on bilateral migration flows and stocks typically hold a small number of time series observations (T) on a moderate number of cross-sections (N). Estimating a dynamic model using such data is particularly challenging. The standard fixed effects (FE) estimator, used by e.g. Hooghe et al. (2008) and Warin and Svaton (2008), is severely biased and inconsistent for T fixed and N going to infinity (see e.g. Nickell, 1981). First-differenced and even system generalized method of moments (GMM) estimators, used by Mayda (2010), are known to suffer from a weak instruments problem (see e.g. Bun and Windmeijer, 2010), which implies a small sample bias, large uncertainty around coefficient estimates and strong sensitivity to instruments choice. We refer to Baltagi (2008) for an overview of dynamic panel data estimators.

In this chapter, we investigate the determinants of bilateral immigration to the OECD from both advanced and developing origin countries between 1998 and

2007 using the OECD's International Migration Database. Our contribution is twofold. First, we estimate a dynamic model of migration using a three-way panel data model. In contrast to the literature and in line with Hatton (1995) we include both lagged migration and migration stock which allows us to separately identify network effects and dynamics stemming from partial adjustment. Second, we estimate this dynamic panel data model using an extended version of the bias-corrected fixed effects (BCFE) estimator suggested by Everaert and Pozzi (2007). This estimator corrects for the dynamic panel data bias of the FE estimator using an iterative bootstrap algorithm. Its main advantage over GMM estimators for dynamic panel data is that it combines a small bias with a relatively small standard error. We slightly adjust the bootstrap algorithm of the BCFE estimator to take into account that in our model the dynamic panel data bias is induced by the lagged migrant flow as well as by the migrant stock. Using Monte Carlo experiments, we demonstrate that this adjusted BCFE estimator performs well in the specific context of our model and is preferable to alternative estimators.

Our results indicate that immigrants are primarily attracted by better income opportunities abroad and much less by income at home and by employment rates both at home and abroad. High public services are found to discourage migration from advanced countries but exert a pull on migration from developing sources, confirming the welfare magnet hypothesis. Furthermore, we find evidence of strong dynamic effects. Both the lagged migration flow and the migrant stock have a strong positive and significant impact on current migration, the former indicating dynamic effects stemming from the process by which expectations about future earnings are formed and updated while the latter indicates network effects. Further evidence that dynamics play a prominent role in the migration model arises from the observation that misspecifying the model by omitting the lagged migration flow or the migrant stock and/or not correcting for the dynamic panel bias has a strong impact on the estimation results. Therefore, care should be taken when specifying the dynamic structure of the model and selecting the estimation method.

The remainder of this chapter is organized as follows. Section 2.2 derives the empirical specification and presents the estimation method with Monte Carlo evidence on its performance. Section 2.3 describes the data and reports the estimation results. Section 2.4 summarizes the major findings.

2.2 A three-way dynamic panel data approach to migration

One of the major contributions to the literature on the determinants of migration has been the traditional push-pull model (see e.g. Lee, 1966; Todaro, 1969; Borjas, 1989). According to this model, migration is the result of push factors at the origin and pull factors at the destination. The migration decision is based on the comparison between expected benefits and costs of migration. A formal dynamic model was developed by Hatton (1995). This model forms the basis for our empirical specification.

2.2.1 A dynamic model of migration

Hatton's model builds on a microeconomic analysis which treats migration as a decision of a utility maximizing individual. A key dynamic feature of the model is that individual i's decision to migrate at time t does not only depend on the current utility, V_t, but also on the net present value of all future utility streams, denoted V_t^*. As such, the total net present value of staying in the origin country o at time t

is given by

$$U_{iot} = \beta \left(\alpha V_{ot} + V_{ot}^{*} \right) + \varepsilon_{ot} \tag{2.1}$$

where $\alpha > 1$ reflects the extra weight given to current conditions and ε_{ot} is an i.i.d. extreme-value distributed random term. Analogously, the net present value of residing in country d at time t can be written as

$$U_{idt} = \beta \left(\alpha V_{dt} + V_{dt}^{*} \right) + \varepsilon_{dt}. \tag{2.2}$$

The utility maximizing individual will choose the country that provides the best opportunities among the home country and all potential destination countries. In line with McFadden (1978), the probability that individual i will migrate from o to d at time t $(m_{idot} = 1)$ can be written as

$$Pr\left(U_{idt} = \max_{k} U_{ikt} \right) = \frac{M_{dot}}{N_{ot}} \tag{2.3}$$

$$= \frac{exp\left(\beta\alpha V_{dt} + \beta V_{dt}^{*} \right)}{\sum_{k} exp\left(\beta\alpha V_{kt} + \beta V_{kt}^{*} \right)} \tag{2.4}$$

where N_{ot} denotes the size of the native population in country o. Analogously, the probability that individual i will stay in country o at time t $(m_{idot} = 0)$ is given by

$$Pr\left(U_{iot} = \max_{k} U_{ikt} \right) = \frac{N_{oot}}{N_{ot}} \tag{2.5}$$

$$= \frac{exp\left(\beta\alpha V_{ot} + \beta V_{ot}^{*} \right)}{\sum_{k} exp\left(\beta\alpha V_{kt} + \beta V_{kt}^{*} \right)} \tag{2.6}$$

where N_{oot} denotes the number of stayers in country o at time t. Combining equations (2.4) and (2.6), aggregate migration from o to d to the resident population in country o is given by

$$\frac{M_{dot}}{N_{oot}} = \frac{exp\left(\beta\alpha V_{dt} + \beta V_{dt}^{*}\right)}{exp\left(\beta\alpha V_{ot} + \beta V_{ot}^{*}\right)} \tag{2.7}$$

or, taking logs,

$$\ln\left(\frac{M_{dot}}{N_{oot}}\right) = \beta\alpha V_{dt} + \beta V_{dt}^{*} - \beta\alpha V_{ot} - \beta V_{ot}^{*} \tag{2.8}$$

$$= \beta\alpha\left(V_{dt} - V_{ot}\right) + \beta\left(V_{dt}^{*} - V_{ot}^{*}\right) \tag{2.9}$$

$$= \beta\alpha d_t + \beta d_t^{*} \tag{2.10}$$

where d_t denotes the current expected utility difference and d_t^* captures expected future utility differences in year t. As suggested by Hatton (1995), the former can be defined as

$$d_t = Eu\left(y_{dt}\right) - Eu\left(y_{ot}\right) + z_{dot} \tag{2.11}$$

where y denotes income and z_{dot} captures the average non-pecuniary utility differences between the two countries as well as the cost of migration. Following Todaro (1969), Hatton defines expected income as the wage (w) times the employment rate (e), with income uncertainty being due to uncertain employment prospects. To take into account the welfare magnet theory presented in Borjas (1987, 1999), we extend this definition of expected income by adding the provision of public services (ps) in the form of social protection benefits[2] (see also Pedersen et al., 2008; Warin and Svaton, 2008). Assuming a logarithmic utility function and a binomial distribution to characterize the probability of employ-

[2]The inclusion of public services might also be linked to the cost of migration, z_{dot}. In that sense, immigrants are expected to prefer countries with a generous system of public services since the presence of a safety net lowers the psychological cost of migration.

ment, equation (2.11) can be rewritten as

$$d_t = \eta_1 \ln w_{dt} - \eta_2 \ln w_{ot} + \eta_3 \ln ps_{dt} + \eta_4 \ln e_{dt} - \eta_5 \ln e_{ot} + z_{dot}. \qquad (2.12)$$

Assuming that expectations about future utility streams are a geometric series of past utility differences[3]

$$d_t^* = \lambda d_t + \lambda^2 d_{t-1} + \lambda^3 d_{t-2} + \lambda^4 d_{t-3} + ... \qquad (2.13)$$

and applying a Koyck transformation gives

$$\ln\left(\frac{M_{dot}}{N_{oot}}\right) = \beta(\alpha+\lambda)d_t - \lambda\beta\alpha d_{t-1} + \lambda \ln\left(\frac{M_{dot-1}}{N_{oot-1}}\right) \qquad (2.14)$$

or, equivalently,

$$\ln M_{dot} = \beta(\alpha+\lambda)d_t - \lambda\beta\alpha d_{t-1} + \lambda \ln M_{dot-1} + \ln\left(\frac{N_{oot}}{N_{oot-1}}\right). \qquad (2.15)$$

Substituting (2.11) in (2.16) and rearranging results in the following aggregate dynamic migration equation

$$\begin{aligned}\ln M_{dot} = {} & \lambda \ln M_{dot-1} + \beta(\alpha+\lambda)(\eta_1 \ln w_{dt} - \eta_2 \ln w_{ot} \\ & + \eta_3 \ln ps_{dt} + \eta_4 \ln e_{dt} - \eta_5 \ln e_{ot} + z_{dot}) \\ & - \lambda\beta\alpha(\eta_1 \ln w_{dt-1} - \eta_2 \ln w_{ot-1} + \eta_3 \ln ps_{dt-1} \\ & + \eta_4 \ln e_{dt-1} - \eta_5 \ln e_{ot-1} + z_{dot-1}) + \ln\left(\frac{N_{oot}}{N_{oot-1}}\right). \qquad (2.16)\end{aligned}$$

[3]As shown by Hatton (1995) this is consistent with rational expectations if d_{it} follows an AR(1) process.

Hatton assumes that z_{dot} is determined by the stock of previous immigrants and a time variable such that

$$z_{dot} = \gamma_0 + \gamma_1 \ln MST_{dot} + \gamma_t + \gamma_{do} \tag{2.17}$$

where MST_{dot} is the stock of migrants from origin country o residing in destination country d at the beginning of time t. This stock variable is included to capture network effects: friends and relatives who already live in the host country reduce the monetary and psychological costs of migration. The higher the stock of previous immigrants from the same origin country, the lower the costs of migration and the higher the immigrant flow. Nevertheless, this is not the only cost determining factor. Also decreasing transportation and communication costs lower the cost of migration over time. In our model, these decreasing costs are captured by the year dummies γ_t. The latter might however also represent, among other things, the impact of joint changes in origin and destination countries' emigration and immigration policies and they also capture the impact of changes in the origin population $\ln(N_{oot}/N_{oot-1})$.[4] Furthermore, also distance, common language, similar culture, colonial ties and immigration policy affect the cost of migration. To the extent that these factors are time invariant, they are captured by the bilateral fixed effect γ_{do}.

The stock of migrants diminishes at a rate δ_{do} due to deaths and return migration

[4]Given that we are not interested in the role of population growth in shaping bilateral migration, we assume equal population growth across countries to get rid of the population ratio in equation (2.16). Moreover, as argued by Egger and Pfaffermayr (2003), a three-way model that includes both bilateral effects and time effects is identical to a model that includes also country specific effects. As such, the empirical model described above indirectly controls for both time-variant and cross-sectional differences in population growth. Consequently, the population ratio can be disregarded without further implications.

but increases due to the inflow of new migrants such that

$$MST_{dot} = (1-\delta_{do})\, MST_{dot-1} + M_{dot-1}. \tag{2.18}$$

where δ_{do} is allowed to vary across destination and origin country pairs. In a later stage, this relationship will be used to account for the link between immigrant flows and stocks. For the moment, we use this expression to eliminate $\ln MST_{dot-1}$ from z_{dot-1} in equation (2.16) by applying a logarithmic expansion of the migrant stock and its components in equation (2.18) about their mean values so that

$$\ln MST_{dot} = (1-\Omega)\ln\left[(1-\delta_{do})\, MST_{dot-1}\right] + \Omega \ln M_{dot-1} \tag{2.19}$$

where $\Omega = \frac{M}{(1-\delta)MST+M} > 0$.[5]

[5] First, we can write $\ln\{MST_{dot}/[(1-\delta_{do})\,MST_{dot-1}]\}$ as $\ln\{1+\exp[\ln M_{dot-1} - (1-\delta_{do})\ln MST_{dot-1}]\}$. A first-order Taylor expansion of the latter around the mean values of M_{dot-1} and $(1-\delta_{do})\,MST_{dot-1}$ gives $\ln\{MST_{dot}/[(1-\delta_{do})\,MST_{dot-1}]\} \approx \Omega\,[\ln M_{dot-1} - (1-\delta_{do})\ln MST_{dot-1}] + c$ where c is an arbitrary constant which we ignore for notational convenience. Now add $\ln[(1-\delta_{do})\,MST_{dot-1}]$ to both sides of the equation to approximate $\ln MST_{dot} = \ln[(1-\delta_{do})\,MST_{dot-1} + M_{dot-1}]$ which gives (2.19) in the text.

Substituting (2.17) and (2.19) in (2.16) and rearranging gives

$$\begin{aligned}
\ln M_{dot} &= \mu_0 + \mu_t + \mu_{do} + \left(1 - \frac{\Omega\beta\alpha\gamma_1}{1-\Omega}\right)\lambda \ln M_{dot-1} \\
&+ \left(\beta\left(\alpha+\lambda\right) - \frac{\beta\alpha\lambda}{1-\Omega}\right)\gamma_1 \ln MST_{dot} \\
&+ \beta\left(\alpha+\lambda\right)\eta_1 \ln w_{dt-1} - \beta\left(\alpha+\lambda\right)\eta_2 \ln w_{ot-1} \\
&+ \beta\left(\alpha+\lambda\right)\eta_3 \ln ps_{dt-1} \\
&+ \beta\left(\alpha+\lambda\right)\eta_4 \ln e_{dt-1} - \beta\left(\alpha+\lambda\right)\eta_5 \ln e_{ot-1} \\
&+ \beta\left(\alpha+\lambda-\alpha\lambda\right)\eta_1 \Delta \ln w_{dt} - \beta\left(\alpha+\lambda-\alpha\lambda\right)\eta_2 \Delta \ln w_{ot} \\
&+ \beta\left(\alpha+\lambda-\alpha\lambda\right)\eta_3 \Delta \ln ps_{dt} \\
&+ \beta\left(\alpha+\lambda-\alpha\lambda\right)\eta_4 \Delta \ln e_{dt} - \beta\left(\alpha+\lambda-\alpha\lambda\right)\eta_5 \Delta \ln e_{ot} + \varepsilon_{dot} \qquad (2.20)
\end{aligned}$$

with $\mu_0 = \beta\left(\alpha+\lambda-\alpha\lambda\right)\gamma_0$, $\mu_t = \beta\left(\alpha+\lambda\right)\gamma_t - \beta\alpha\lambda\gamma_{t-1}$ and $\mu_{do} = \beta\left(\alpha+\lambda-\alpha\lambda\right)$ $\gamma_{do} + \beta\lambda\alpha\gamma_1 \ln\left(1-\delta_{do}\right)$.

A number of key features of this model are worth discussing. First, note that equation (2.20) is of the double log form, which results from the choice of functional form for the utility function and from taking migration and the migrant stock in equations (2.14) and (2.17) as logarithmic. Although Hatton's (1995) original model is semi-logarithmic, he emphasizes that this model is only one among many different functional forms and also suggests and estimates a double log version. Given our panel dataset, with countries that greatly differ in size, the double log form has the important advantage that it eliminates the scale of the migrant flows and stocks. As an alternative, some studies divide the immigrant flow by the population in the origin or destination countries (see e.g. Fertig, 2001; Boeri et al., 2002; Pedersen et al., 2008; Mayda, 2010), but this only partly removes problems of scale. Only dividing by the population in both sending and receiving countries or taking the natural logarithm entirely solves the problem (see Lewer and Van den Berg, 2008; Warin and Svaton, 2008; Ortega and Peri, 2009).

Second, lagged migration flow and migrant stock enter equation (2.20) as two separate determinants. This contradicts the common practice in empirical studies to include either the lagged migration flow (see e.g. Bertocchi and Strozzi, 2008; Mayda, 2010) or the migrant stock (see e.g. Hooghe et al., 2008; Lewer and Van den Berg, 2008; Pedersen et al., 2008; Warin and Svaton, 2008), with both variables typically being argued to capture network effects[6]. Laber (1972) has already highlighted that it is not clear whether these dynamic terms represent network effects or rather capture a partial adjustment mechanism. Dunlevy and Gemery (1977) argue that lagged migration and migrant stock should both be included as determinants to capture the separate impact of partial adjustment and network effects respectively. This is confirmed by equation (2.20) which shows that a nonzero coefficient on $\ln M_{dot-1}$ implies partial adjustment ($\lambda \neq 0$) stemming from the process by which expectations are formed and updated while a nonzero coefficient on $\ln MST_{dot}$ implies network effects ($\gamma_1 \neq 0$).

Third, an additional dynamic feature of the model is that it includes both lagged levels and current changes of the explanatory variables. The latter capture immediate responses of the immigrant flow to changes in the explanatory variables. This stems from the fact that migration decisions can be postponed when economic conditions are unfavorable such that migration may fluctuate more closely with current conditions than might be expected from individuals that maximize their lifetime utilities.

[6]A popular motivation for not including both lagged migrant flow and migrant stock is that the latter is, as presented in equation (2.18), the sum of all past immigrant flows less deaths and return migrants. Hence, the migrant stock is itself a function of all those factors which influenced the earlier immigrant flows. Therefore it will be correlated with all the explanatory variables. However, multicollinearity is no reason to omit the migrant stock variable as this may result in a specification bias as well as in a loss of information regarding the network effect.

2.2.2 Empirical specification and long-run effects

The unrestricted form of equation (2.20) is given by

$$\begin{aligned}\ln M_{dot} &= \mu_{do} + \mu_t + \theta_1 \ln M_{dot-1} + \theta_2 \ln MST_{dot} + \theta_3 X_{dot-1} + \theta_4 \Delta X_{dot} + \varepsilon_{dot} \\ &= \mu_{do} + \mu_t + \theta W'_{dot} + \varepsilon_{dot} \qquad (2.21)\end{aligned}$$

where $\theta = (\theta_1, \theta_2, \theta_3, \theta_4)$ and $W_{dot} = (\ln M_{dot-1}, \ln MST_{dot}, X_{dot-1}, \Delta X_{dot})$ with X_{dot} capturing all determinants of migration other than $\ln M_{dot-1}$ and $\ln MST_{dot}$ included in equation (2.20). The error terms ε_{dot} are assumed to be serially uncorrelated but allowed to be heteroscedastic between and contemporaneously correlated over cross-sections. Both the lagged migration flow $\ln M_{dot-1}$ and the migrant stock $\ln MST_{dot}$ (which is measured at the beginning of time t) are predetermined at time t and therefore not correlated with the error term ε_{dot}. By construction, both these variables are correlated with the individual effects μ_{do}. All other regressors are allowed to be correlated with μ_{do} but are assumed to be exogenous with respect to ε_{dot}. The latter assumption is based on the fact that we investigate the determinants of bilateral immigrant flows, i.e. at a disaggregated level, which will have only a small impact on the macroeconomic determinants of migration like e.g. wages and employment. The semi long-run impact of the explanatory variables on migrant flows can be obtained by imposing a no change constraint on equation (2.21), i.e. imposing $\ln M_{dot} = \ln M_{dot-1}$, $\varepsilon_{dot} = 0$ and setting differences to zero, which gives

$$\ln M_{dot} = \frac{1}{1-\theta_1} \left(\mu_{do} + \mu_t + \theta_2 \ln MST_{dot} + \theta_3 X_{dot} \right). \qquad (2.22)$$

Yet, these are not the full long-run effects as they ignore the endogeneity of the migrant stock $\ln MST_{dot}$. The full long-run impact is obtained by simulating the dynamic response[7] of $\ln M_{do}$ and $\ln MST_{do}$ to a 1% increase in each of the explanatory variables in X_{do} using the estimated equation (2.21) together with equation (2.18) with $\delta = \frac{1}{N}\sum_{do}\delta_{do}$.

2.2.3 Choice of dynamic panel data estimator

The empirical specification in equation (2.21) is dynamic in the sense that it incorporates both the lagged migrant flow and the migrant stock as explanatory variables. Estimation of dynamic panel data models has received a lot of attention in the literature. The main problem is that the lagged dependent variable is by construction correlated with the individual effects. This renders the pooled ordinary least-squares (POLS) estimator biased and inconsistent. A within transformation wipes out the individual effects by taking deviations from individual sample means, but the resulting FE estimator is biased and inconsistent for fixed T and N going to infinity (see Nickell, 1981). Given this inconsistency, the literature focuses mainly on a first-difference transformation to eliminate the individual effects while handling the remaining correlation with the (transformed) error term using instrumental variables (IV) and GMM estimators. Especially the first-differenced GMM estimator of Arellano and Bond (1991) and the system GMM estimator of Arellano and Bover (1995) and Blundell and Bond (1998) are popular. The advantage of these estimators is that they are consistent for fixed T and large N. Unfortunately, these GMM estimators (i) have a (much) larger standard error compared to the FE estimator (see e.g. Arellano and Bond, 1991; Kiviet, 1995) and (ii) may suffer from a substantial finite sample bias due to weak instrument problems (see Ziliak, 1997; Bun and Kiviet, 2006; Bun and Windmeijer, 2010). In order to avoid these problems, analytical bias-corrections for the FE

[7]The long-run impact is defined from imposing a no change condition, i.e. the criterion that the squared difference between two subsequent values of the dynamic response should be less than or equal to 0.0001^2.

estimator have been proposed by, among others, Kiviet (1995), Bun (2003) and Bun and Carree (2005). The advantage of these estimators is that they reduce the bias of the FE estimator while maintaining its small dispersion relative to GMM. Although these estimators perform remarkably well, even in samples of moderate T, the use of analytical corrections in practical applications may be limited as the theoretical restrictions under which these corrections are derived do not necessarily hold. A detailed overview of dynamic panel data estimators can be found in Baltagi (2008).

As an alternative, Everaert and Pozzi (2007) propose a bias-correction for the FE estimator using an iterative bootstrap algorithm. Like analytical corrections, this bootstrap correction reduces the bias of the FE estimator while maintaining its higher efficiency compared to GMM estimators. The main advantage is that it can more easily be adjusted to practical applications by an appropriate choice of the data resampling scheme. This flexibility is of particular interest for estimating our empirical specification where next to the lagged migration flow also the migration stock is by construction correlated with the individual effects. This is a case which is not considered by the analytical corrections. Therefore, the bootstrap-based bias-corrected FE estimator is our main estimator used below. We refer to it as BCFE.

2.2.4 Implementation of the BCFE estimator

Without going in too much technical details (for this we refer to Everaert and Pozzi, 2007), the basic BCFE estimator searches over the parameter space and takes as bias-corrected estimates the set of parameters $\tilde{\theta}$ for which holds that when repeatedly generating artificial data from equation (2.21) setting $\theta = \tilde{\theta}$ and next estimating this equation from these artificial data using FE yields on average (over repeated samples) the original biased FE estimates $\hat{\theta}$. In practice, this search over the parameter space is computationally implemented through an iterative bootstrap algorithm, initiated by setting as a first guess $\tilde{\theta}^0 = \hat{\theta}$, which is used to generate 1000 bootstrap data samples from equation (2.21) setting $\theta = \tilde{\theta}^0$. These artificial data are then used to calculate the bias of the FE estimator as $\tilde{\theta}^0 - \bar{\theta}^1$ where $\bar{\theta}^1$ is the average of the 1000 FE estimates obtained over the bootstrap samples. The first step bias-corrected FE estimator is then given by $\tilde{\theta}^1 = \hat{\theta} + \left(\tilde{\theta}^0 - \bar{\theta}^1\right)$. In the second step, this bias-correction procedure is repeated but now data are generated by setting $\theta = \tilde{\theta}^1$ from which we obtain the bias as $\tilde{\theta}^1 - \bar{\theta}^2$ (with obvious notation) and the second step bias-corrected FE estimator as $\tilde{\theta}^2 = \hat{\theta} + \left(\tilde{\theta}^1 - \bar{\theta}^2\right)$. This procedure is then iterated until convergence, i.e a stable set of parameter values $\tilde{\theta}^k \approx \tilde{\theta}^{k+1}$ is obtained.

The artificial data generated in the algorithm outlined above are obtained using a semi-parametric procedure, i.e. bootstrap samples $\tilde{\varepsilon}^b_{dot}$ are obtained by a non-parametric resampling of the (rescaled) estimated residuals $\hat{\varepsilon}^k_{dot}$ (obtained using $\tilde{\theta}^k$) while bootstrap samples for M^b_{dot} are calculated from the parametric model in equation (2.21) setting $\theta = \tilde{\theta}^k$. As stated above, this data resampling procedure has the important advantage that it can easily be shaped to align with the assumed data generating process of the data. First, the non-parametric resampling of $\hat{\varepsilon}^k_{dot}$ does not require explicit distributional assumptions for the population errors ε_{dot} such that, in line with our assumptions in Section 2.2.2, we allow for (i) heteroscedasticity over cross-sections by resampling residuals within but not between cross-section units and (ii) contemporaneous correlation between cross-sections by applying the same resampling index to each cross-section. Second, next to calculating bootstrap samples M^b_{dot} for the migrant flow from equation (2.21), we also calculate bootstrap samples MST^b_{dot} for the migrant stock using equation (2.18) setting $\delta_{do} = 1 - \frac{1}{T}\sum_t \left(\left(MST_{dot} - M_{dot-1}\right)/MST_{dot-1}\right)$. This captures the important feature that MST_{dot} is endogenous, i.e. correlated with the individual effects. Further note that in line with the assumption in Section 2.2.2 that all explanatory variables other than M_{dot} and MST_{dot} are exogenous, these are kept fixed over the bootstrap samples.

2.2.5 Monte Carlo simulation

In this Section we conduct a small-scaled Monte Carlo experiment to assess the finite sample properties of our adjusted BCFE estimator compared to several other estimators.

Design

The data generating process (DGP) is chosen such that the properties of the simulated data match with those of the observed data as much as possible:

- The sample size of the simulated data equals the one available for estimation. This implies running separate simulations for advanced ($T = 9, N = 247$) and developing ($T = 9, N = 388$) origin countries.

- Data for the endogenous variables migration flow M_{dot} and migration stock MST_{dot} are drawn from their data generating process (DGP) in equations (11) and (8) respectively, using the observed values in the first year of the sample as initialisation.

- The parameter values for θ in the DGP for M_{dot} in equation (11) are set equal to the BCFE estimates from Table 3 below while δ_{do} in equation (8) is set equal to the value observed in the sample data.

- Error terms ε_{dot} are generated from a normal distribution with estimated variance from the residuals of the BCFE regressions in Table 3.

- The observed values for the exogenous variables X_{dot-1} and ΔX_{dot} are treated as fixed in each MC iteration.

We generate data both for the full model and for a partial model with only stocks and lagged flows as explanatory variables ($\theta_3 = \theta_4 = 0$ in equation (2.21)). This results in four experiments with the coefficients for lagged flows, θ_1, and stocks, θ_2, respectively set to 0.61 and 0.46 (0.64 and 0.49) for the complete (partial) model using the advanced dataset, and 0.75 and 0.23 (0.74 and 0.23) for the complete (partial) model using the developing dataset. In each experiment, we perform 1000 replications.

Estimators

We compare the performance of the BCFE estimator with (i) FE, the standard fixed effects estimator, (ii) GMMd, the first-difference GMM estimator proposed by Arellano and Bond (1991) and (iii) GMMs, the system GMM estimator proposed by Arellano and Bover (1995) and Blundell and Bond (1998). For the GMMd estimator, at least one period lagged values ($\ln M_{dot-1-s}$ and $\ln MST_{dot-s}$ with $s \geq 1$) are available as instruments for the predetermined variables $\ln M_{dot-1}$ and $\ln MST_{dot}$[8] in each period. For the exogenous variables X_{dot-1} and ΔX_{dot}, the available instruments set is $(X_{do1}, \ldots, X_{doT-1}, \Delta X_{do2}, \ldots, \Delta X_{doT})$ in each period. GMMs has the same instrument set as GMMd in the first difference part of the system and has $\Delta \ln M_{dot-2}$, ΔX_{dot-1} and $\Delta^2 X_{dot}$ as additional instruments in the levels part of the system. Note that the first-differenced stock $\Delta \ln MST_{dot-1}$ can not be used as instrument as it is by construction correlated with the fixed effect μ_{do} in the levels equation. Given the large number of exogenous variables, we try to avoid an overfitting bias resulting from using too many instruments (see Ziliak, 1997; Arellano, 2003) by (i) only using the first three available instruments

[8] Ln MST_{dot} is predetermined as it is defined as the migrant stock at the beginning of the period.

for the predetermined variables ($\ln M_{dot-1}$ and $\ln MST_{dot}$) and the contemporaneous values for the exogenous variables and (ii) stacking the instrument matrix as suggested by Roodman (2009). We report both one-step and two-step GMM estimates.

Simulation results

The simulation results are presented in Tables 2.1 and 2.2. For each estimator, we report mean bias, standard deviation (Std) and root mean squared error (Rmse) in estimating θ_1 and θ_2.

First looking at the performance in estimating θ_1, we observe the following results for both types of models. As expected, the FE estimator is biased downward because of the correlation between the transformed lagged dependent variable and the transformed error term. Correcting for the dynamic panel bias by performing BCFE significantly reduces the bias while maintaining the low dispersion associated with the uncorrected FE. The bias of the GMMd1 and GMMd2 estimators is of the same order as in BCFE, but they have a much larger dispersion and rmse. The GMMs estimators have a sizable bias in all cases. This suggests that the extra moment conditions imposed in the level part of the system, from a restriction on the initial conditions process generating $\ln M_{do1}$, is violated.

Second, regarding the relative performance in the estimation of θ_2, the GMMd estimators have the smallest bias, followed by the FE and BCFE estimators. However, the standard deviation of the GMMd estimators is always bigger compared to the FE and BCFE estimators. This results in (i) the lowest rmse for the BCFE estimator using the advanced dataset and the partial model developing dataset and (ii) a fairly similar rmse for the BCFE and GMMd estimates for the complete model developing dataset. The GMMs estimators again have a sizable bias in most cases.

Table 2.1: Monte Carlo results based on database with advanced origins ($T = 9, N = 247$)

	Bias θ_1	Std θ_1	Rmse θ_1	Bias θ_2	Std θ_2	Rmse θ_2
Full model, θ_1 = 0.61 and θ_2 = 0.46						
FE	-0.192	0.021	0.193	0.035	0.047	0.059
BCFE	-0.011	0.025	0.028	-0.026	0.045	0.052
GMMd1	-0.014	0.138	0.138	0.003	0.064	0.064
GMMd2	-0.014	0.141	0.141	0.002	0.065	0.065
GMMs1	0.226	0.026	0.228	-0.249	0.031	0.251
GMMs2	0.200	0.031	0.202	-0.204	0.042	0.208
Partial model with $\theta_3 = \theta_4 = 0$, θ_1 = 0.64 and θ_2 = 0.49						
FE	-0.185	0.021	0.186	0.079	0.044	0.091
BCFE	-0.011	0.025	0.028	-0.024	0.043	0.049
GMMd1	-0.006	0.076	0.076	0.002	0.066	0.066
GMMd2	-0.005	0.076	0.076	0.001	0.066	0.066
GMMs1	-0.112	0.070	0.132	-0.090	0.062	0.109
GMMs2	-0.099	0.071	0.122	-0.103	0.065	0.122

Notes: θ_1 and θ_2 denote the coefficients for $\ln M_{dot-1}$ and $\ln MST_{dot}$, respectively. θ_3 and θ_4 represent the coefficients of the strictly exogenous variables. For the GMM estimators, '1' refers to one-step estimates and '2' refers to two-step estimates.

In conclusion, due to its small bias combined with a relatively small standard deviation, the BCFE estimator is shown to outperform the alternative estimators in terms of rmse given the specificities of our model and sample data. As such, we take it as our preferred estimator in the next section.

2.3 Data and estimation results

2.3.1 Data

Data on bilateral immigrant flows and stocks are taken from the International Migration Database provided by the OECD. It contains information on inflows of foreigners by nationality and stocks of foreigners by both nationality and country of birth to 19 OECD countries from 189 origin countries over the period 1998-2007.

Table 2.2: Monte Carlo results based on database with developing origins ($T = 9, N = 388$)

	Bias θ_1	Std θ_1	Rmse θ_1	Bias θ_2	Std θ_2	Rmse θ_2
Full model, θ_1 = 0.75 and θ_2 = 0.23						
FE	-0.159	0.016	0.159	-0.117	0.048	0.127
BCFE	-0.018	0.018	0.025	-0.099	0.044	0.109
GMMd1	-0.024	0.152	0.154	-0.016	0.104	0.105
GMMd2	-0.022	0.153	0.155	-0.017	0.106	0.107
GMMs1	0.162	0.020	0.163	-0.212	0.027	0.214
GMMs2	0.137	0.023	0.139	-0.181	0.032	0.184
Partial model with $\theta_3 = \theta_4 = 0$, θ_1 = 0.74 and θ_2 = 0.23						
FE	-0.136	0.015	0.137	0.039	0.037	0.054
BCFE	-0.007	0.017	0.018	-0.028	0.035	0.045
GMMd1	-0.000	0.042	0.042	-0.002	0.055	0.055
GMMd2	-0.000	0.042	0.042	-0.002	0.056	0.056
GMMs1	0.001	0.042	0.042	-0.013	0.034	0.036
GMMs2	0.000	0.042	0.042	-0.013	0.034	0.036

Notes: see Table 2.1.

For the migrant stock, we use data on foreign-born by country of birth wherever possible and foreign nationals otherwise. In order to account for potential heterogeneity, we divide our sample of origins into advanced and developing countries following IMF definitions. While the IMF distinguishes between advanced countries on the one hand and developing and emerging countries on the other hand, we combine the second group and refer to it as developing countries. Table 2.5 reports total yearly immigrant flows into each destination country between 1998 and 2007. After removing cross-sections with missing observations and with obvious inconsistencies between flows and stocks, we have 247 cross-sections for advanced origins and 388 cross-sections for developing origins. Tables 2.6 and 2.7 show that these account for 16.5 percent and 58.5 percent respectively of the total flow. Hence, migration from developing countries clearly dominated during our sample period.

Table 2.8 presents descriptive statistics for all variables used in the regression analysis. Due to a lack of real wage data for the set of origin countries, wages are approximated by per capita gross domestic product (see also Fertig, 2001; Pedersen et al., 2008; Mayda, 2010), expressed in current dollars purchasing power parities to correct for differences in the evolution in the cost of living between countries. Data on GDP per capita are taken from the Penn World Tables 6.3. The employment rate is proxied by the number of employed relative to the population, as provided by the United Nations Statistics Division. One could argue that the general employment rate does not capture the true labor market constraints faced by immigrants due to the presence of a home bias in the demand for labor. One possibility is to replace it by the employment rate for foreigners in the destination country. However, this rate does not eliminate measurement error since it does not discriminate between foreigners from the developing world and those from advanced countries. Consequently, we stick to the general employment rate to proxy for employment possibilities for immigrants in the host country. Public services in the destination country are proxied by expenditures of social protection benefits for sickness/health care and family/children allowances, expressed as a percentage of GDP. Generally public expenditures include also other types of benefits such as those for disability, old age, unemployment or housing. Yet, access to those benefits for new entrants is typically constrained and therefore excluded from our proxy for public expenditures. The data on public expenditures were obtained from the Social Expenditure Database (SOCX), provided by the OECD.

2.3.2 Estimation results

The estimation results are reported in Table 2.3. To allow for a heterogeneous impact of migration determinants, separate results are reported for migration from advanced and from developing countries. Our preferred methodology is BCFE estimation of equation (2.21). The standard errors used to calculate the t-statistics are simulated using the bootstrap algorithm as outlined in Everaert and Pozzi (2007). They are robust to both cross-sectional heteroscedasticity and cross-sectional error correlation. To link our results to those in the literature, we also report results from (i) FE estimation of restricted versions of equation (2.21) including either lagged migration or the migrant stock and (ii) FE estimation of equation (2.21) not correcting for the dynamic panel data bias. For these estimators, standard errors are simulated in a similar way as for the BCFE estimator.[9]

We also experimented with GMMd and GMMs estimations but these were unsatisfactory as the results were highly sensitive to the choice of instruments. Consequently, we do not discuss the GMM results but some of the results can be found in Table 2.9 in the Appendix. One interesting point to note though is that, in line with the results from the Monte Carlo simulation, the Sargan-Hansen test rejects the validity of the moment conditions underlying the GMMs estimator. Furthermore, we tested if the model specification in equation (2.21) is appropriate by adding the second lag of $\ln M_{dot}$ to the estimation equation. The coefficient for the second lag of $\ln M_{dot}$ turned out insignificant for both advanced and developing origins, yet the first lag remained significant indicating that our results are robust for this alternative specification[10].

Table 2.4 reports long-run elasticities of migration determinants calculated from the BCFE estimation results. The first three columns report semi long-run effects, while the last three columns report full long-run effects. With respect to the latter, it should be noted that they are calculated assuming the strong link between flows and stocks as given in equation (2.18). In our dataset this link is less strong, though, as stock data are not constructed from the flow data such that the evolution

[9]The matlab code for the BCFE estimator is available upon request.

[10]The estimation results for this model are available upon request.

Table 2.3: Estimation results

Dependent variable: $\ln M_{dot}$ — Sample period: 1998-2007

	Advanced origins				Developing origins			
	FE(1)	FE(2)	FE(3)	BCFE	FE(1)	FE(2)	FE(3)	BCFE
$\ln MST_{dot}$		0.73^{***}	0.44^{***}	0.46^{***}		0.82^{***}	0.24^{***}	0.23^{***}
		(6.19)	(4.82)	(6.10)		(7.75)	(4.54)	(4.55)
$\ln M_{dot-1}$	0.48^{***}		0.44^{***}	0.61^{***}	0.65^{***}		0.61^{***}	0.75^{***}
	(9.38)		(7.58)	(8.51)	(27.67)		(24.02)	(13.50)
$\ln w_{dt-1}$	0.98^{***}	0.93^{**}	0.70^{***}	0.59^{**}	1.92^{***}	2.78^{***}	1.82^{***}	1.58^{***}
	(3.45)	(2.00)	(2.59)	(2.32)	(5.82)	(4.08)	(5.43)	(4.89)
$\ln w_{ot-1}$	-0.30	-0.29	-0.34^{*}	-0.37^{**}	0.08	0.15	0.05	0.00
	(-1.53)	(-1.00)	(-1.75)	(-2.20)	(0.81)	(0.82)	(0.53)	(0.02)
$\ln ps_{dt-1}$	-0.24	-0.39	-0.41^{**}	-0.49^{***}	0.66^{**}	0.86^{*}	0.58^{*}	0.37
	(-1.39)	(-1.58)	(-2.40)	(-2.95)	(2.22)	(1.68)	(1.86)	(1.19)
$\ln e_{dt-1}$	1.06^{*}	2.56^{***}	0.96	0.26	-0.29	1.86^{**}	-0.69	-1.56^{**}
	(1.81)	(3.11)	(1.63)	(0.46)	(-0.58)	(2.12)	(-1.45)	(-2.30)
$\ln e_{ot-1}$	0.10	0.31	0.30	0.29	-0.18	-0.30	-0.17	-0.17
	(0.27)	(0.54)	(0.79)	(0.84)	(-0.75)	(-0.69)	(-0.72)	(-0.78)
$\ln \Delta w_{dt}$	1.34^{***}	1.56^{**}	1.40^{***}	1.51^{***}	2.07^{***}	2.47^{***}	2.21^{***}	2.45^{***}
	(2.83)	(2.37)	(2.75)	(2.85)	(4.35)	(3.22)	(4.82)	(5.00)
$\ln \Delta w_{ot}$	-0.02	0.16	-0.06	-0.22	0.12	0.09	0.10	0.08
	(-0.08)	(0.46)	(-0.24)	(-0.85)	(0.99)	(0.56)	(0.82)	(0.59)
$\ln \Delta ps_{dt}$	0.52^{**}	0.60^{**}	0.55^{**}	0.55^{**}	1.08^{***}	0.82^{*}	1.15^{***}	1.33^{***}
	(2.16)	(1.99)	(2.32)	(2.06)	(3.30)	(1.64)	(3.72)	(3.96)
$\ln \Delta e_{dt}$	2.31^{***}	3.14^{***}	2.53^{***}	2.18^{***}	2.82^{***}	1.90^{*}	2.35^{***}	1.89^{*}
	(3.35)	(3.79)	(3.84)	(3.12)	(3.13)	(1.82)	(2.62)	(1.79)
$\ln \Delta e_{ot}$	1.26^{*}	2.11^{***}	1.10^{*}	0.76	0.13	0.34	0.14	0.05
	(1.87)	(2.55)	(1.65)	(1.13)	(0.37)	(0.69)	(0.40)	(0.15)

Notes: Each regression includes time dummies (not reported). t-statistics - between brackets - are robust to cross-sectional heteroskedasticity and cross-sectional error correlation. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively. *Advanced:* 2223 observations and 247 cross sections. *Developing:* 3492 observations and 388 cross sections.

in flows and stocks is not fully compatible. The exact numbers of the full long-run effects reported in Table 2 should therefore be interpreted with care. Standard errors for the long-run effects are also simulated using the bootstrap algorithm. In line with Everaert and Pozzi (2007), we report the median and the 5^{th} and 95^{th}

percentiles of the simulated distribution of the long-run effects rather than the mean and the t-statistic. The reason for this is that the distribution of the long-run effects does not necessarily have finite moments, especially when the root of the dynamic process is close to unity. It should be noted that these percentiles are not necessarily finite either but they should be less vulnerable to large outliers in the distribution.

Table 2.4: Long-run estimation results

Dependent variable: $\ln M_{do}$						Sample period: 1998-2007
	Semi LR (BCFE)			Full LR (BCFE)		
		percentiles			percentiles	
	median	5th	95th	median	5th	95th
Advanced origins						
$\ln MST_{dot}$	0.93***	0.68	1.25	0.00	0.00	0.00
$\ln w_{dt}$	1.64**	0.52	3.26	5.32***	1.72	2.27
$\ln w_{ot}$	−0.95*	−1.79	−0.19	−2.00**	−3.26	−3.06
$\ln ps_{dt}$	−1.19***	−2.00	−0.48	−2.31***	−3.60	−3.33
$\ln e_{dt}$	1.19	−1.81	3.03	3.67	−3.15	−2.15
$\ln e_{ot}$	1.02	−0.66	2.40	2.23	−1.46	−0.69
Developing origins						
$\ln MST_{dot}$	1.01***	0.56	1.54	0.00	0.00	0.00
$\ln w_{dt}$	7.00***	4.36	10.31	14.82***	7.62	28.57
$\ln w_{ot}$	0.04	−0.76	0.56	0.15	−1.12	0.79
$\ln ps_{dt}$	1.93	0.02	4.65	3.17*	0.29	8.44
$\ln e_{dt}$	−7.95**	−15.49	−1.99	−5.55**	−12.57	−1.03
$\ln e_{ot}$	−0.64	−2.41	0.89	−0.72	−2.35	0.96

Note: *, ** and *** indicate significance at the 10%, 5% and 1% level respectively.

Dynamic features of migration

Consistent with the findings in for instance Fertig (2001), Clark et al. (2002) and Pedersen et al. (2008), lagged migrant flows and migrant stocks appear to have the most pervasive impact on subsequent migration from both advanced and developing countries. The results from our preferred BCFE estimator suggest an elasticity of 0.61 (0.75) for lagged migrant flows from advanced (developing) countries and 0.46 (0.23) for the stock of migrants from advanced (developing) countries. The fact that both are significant indicates that multicollinearity between these two variables is fairly small. In correspondence to earlier findings in (Dunlevy and Gemery, 1977) it seems that these variables do not measure the same phenomenon, supporting their simultaneous inclusion in the estimation equation. The significant coefficient on lagged migration flows suggests dynamic effects stemming from the process by which expectations about future earnings are formed and updated while the significant coefficient on migrant stock indicates network effects. Moreover, it is interesting to note that both levels and first-differences of the explanatory variables turn out significant. This suggests that even though migration is essentially a forward-looking decision, it also strongly fluctuates with short-run cyclical conditions rather than being a steady flow.

With respect to the dynamic specification of the model and the estimation procedure, two points are worth mentioning. First, misspecifying the model especially by omitting lagged migration has a strong impact, most notably on the coefficients of the migrant stock which (looking at the FE estimates) increase from 0.44 (0.24) to 0.73 (0.82) for migration from advanced (developing) countries. Misspecifying the model by omitting the migrant stock results in a less pronounced increase in the coefficient on the lagged migrant flow. Second, correcting for the dynamic panel bias is very important for the coefficient on the lagged migrant flow, which rises from 0.44 (0.61) to 0.61 (0.75) for migration from advanced (developing) countries. Also the coefficients on the other determinants are affected by misspecifying dynamics and/or ignoring the dynamic panel data bias. Especially employment rates in the host country are only then found to be significantly positive for migration from both advanced and developing countries.

All these findings indicate that dynamics play a prominent role in the migration model and should definitely not be ignored, both when specifying the model and selecting the estimation method. Below, we discuss the estimation results for the determinants income and employment separately, focusing on the BCFE estimator.

Income

First, consistent with the findings in the empirical literature (see also Karemera et al., 2000; Mayda, 2010), per capita income in the destination country turns out to be one of the key incentives for migration to OECD countries. For both changes and levels, the coefficient is positive and highly significant across sources of migration. This finding is also robust over the different specifications and estimation methods. Looking at the coefficients on the first-differences, a 1 percent rise in per capita income in the destination country results in a 1.51 (2.45) percent immediate temporary rise in the migrant flow from advanced (developing) countries. The coefficients on the one year lagged per capita income show that this 1 percent increase attracts an additional 0.59 (1.58) percent migrants from advanced (developing) source countries in the next year. In the long run (see Table 2.4), this amounts to a 1.64 (7.00) percent increase in the migrant flow when only taking into account dynamics through the lagged migrant flow (semi long-run effects) and even to a 5.32 (14.82) percent increase when also taking into account the link between flows and stocks (full long-run effects). This suggest that taking into account network effects when calculating long-run effects is very important. However, as noted above the exact numbers for the full long-run effects should be considered with care due to the somewhat loose connection between flows and stocks in our dataset.

Second, evidence for the impact of per capita income in the source country is less evident. Both in the short and in the long run, the estimates indicate a statistically significant negative impact on migration for lagged per capita income in advanced origins, but an insignificant impact for per capita income in developing origins (see also Mayda, 2010). First-differenced per capita income at home does not influence the size of migrant flows.

Third, the impact of public services in the destination country is more ambiguous. Immigrants from advanced origin countries prefer destinations with lower levels of public services: the level of public services has a statistically significant elasticity of -0.49 which results in a semi long-run elasticity of -1.19 percent and a full long-run elasticity of -2.31 percent. This finding might be explained by the fact that immigrants from advanced countries consider more public services to go together with more social expenditures which can only be financed by higher taxes. In the short run, the level of public services does not appear to have an impact on migration from developing countries, but the immediate response to an increase in public services, as captured by its first-difference, is found significantly positive. In the long run, however, the level of public services does appear significant with the expected positive sign. Immigrants from developing countries may look upon public services as a safety net and move to countries where public services become more generous, in correspondence with the welfare state hypothesis (see also Borjas, 1999).

Employment

Migration from advanced countries seems independent of the actual level of employment rates at home and abroad, and responds only in the short term to changes in the employment opportunities in the host country. In fact, for immigrants from advanced countries the coefficient of changes in the host country's employment rate is the largest of all coefficients. Furthermore, also immigrants from developing countries respond positively to higher employment growth in the destination, though with a smaller and less significant coefficient. On average, a 1 percent higher growth in the host country's employment rate results in a temporary increase in the bilateral migrant flow from advanced (developing) countries by 2.18 (1.89) percent. Against expectations, however, our estimates suggest that migrants from developing countries generally move to countries where employment opportunities are lower. The same result is obtained in the long run, but the coefficient decreases when the link between stocks and flows is accounted for.

2.4 Conclusions

In this chapter we analyze the determinants of international migration to 19 OECD countries from both advanced and developing origin countries between 1998 and 2007 using the OECD's International Migration Database. The contribution of this chapter is twofold. First, we estimate a dynamic model of migration based on Hatton's (1995) model using a three-way panel data model. This framework allows to control for observed and unobserved time invariant bilateral effects like geographical, historical, political and cultural influences as well as for time effects like cyclical influences, policy changes, decreases in transportation and communication costs, ..., which are common for all country pairs and reduce the risk of biased results. Including both lagged migration and migrant stocks allows us to separately identify network effects and dynamics stemming from partial adjustment. Second, we estimate this dynamic panel data model using an extended version of the iterative bootstrap algorithm suggested by Everaert and Pozzi (2007). This estimator allows us to correct for the dynamic panel data bias of the FE estimator, which in our model is induced by the lagged migrant flow as well as by the migrant stock, and explicitly takes into account the dynamic relationship between immigrant flows and stocks.

Our results strongly confirm the hypotheses of the human capital theory as well as the network theory of migration, though with a few exceptions. We find that recent immigration to the OECD is primarily driven by better income opportunities in the member states. The influence of income at home and employment rates both at home and abroad is much less pronounced. More specifically, our estimates suggest that immigrants from developing countries are primarily driven by per capita GDP in the host country, whereas variations in migration from advanced countries are determined largely by short-run fluctuations in employment rates abroad. Moreover, as expected, higher native wages in advanced countries seem to discourage immigration, but we find no evidence for an impact of home wages in developing countries.

Furthermore, migrants from advanced countries are unlikely to move to countries with high public services due to the link between social expenditures and tax rates. This is not the case for migrants from developing countries, who consider public expenditures a safety net and prefer countries with rising social expenditures, providing some indication for the welfare magnet hypothesis.

Finally, we find evidence of strong dynamic effects. Both the lagged migration flow and the migrant stock have a strong positive and significant impact on current migration, the former indicating dynamic effects stemming from the process by which expectations about future earnings are formed and updated while the latter indicates network effects. Further evidence that dynamics play a prominent role in the migration model arises from the observation that misspecifying the model by omitting the lagged migration flow or the migrant stock and/or not correcting for the dynamic panel bias has a strong impact on the estimation results. Therefore, care should be taken when specifying the dynamic structure of the model and selecting the estimation method.

2.5 Appendix

Table 2.5: Total yearly immigrant flows in our sample of destination countries (thousands)

Destination	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	Total
Australia	94.2	101.0	111.3	131.2	121.2	125.9	150.0	167.3	179.8	191.9	1373.8
Austria	59.2	72.4	66.0	74.8	92.6	97.2	108.9	101.5	85.4	92.0	850.0
Belgium	50.7	57.8	57.3	66.0	70.2	68.8	72.4	77.4	83.4	93.4	697.4
Czech Republic	7.9	6.8	4.2	11.3	43.6	57.4	50.8	58.6	66.1	102.5	409.2
Denmark	21.3	20.3	22.9	25.2	22.0	18.7	18.8	20.1	24.0	26.2	219.5
Finland	8.3	7.9	9.1	11.0	10.0	9.4	11.5	12.7	13.9	17.5	111.3
Germany	605.5	673.9	648.8	685.3	658.3	601.8	602.2	579.3	558.5	574.8	6188.4
Hungary	16.1	20.2	20.2	20.3	18.0	19.4	22.2	25.6	19.4	22.6	204.0
Italy	111.0	268.0	271.5	232.8	388.1	353.7	319.3	206.8	181.5	252.4	2585.1
Japan	265.5	281.9	345.8	351.2	343.8	373.9	372.0	372.3	325.6	336.6	3368.6
Korea	211.2	198.3	185.4	172.5	170.9	178.3	188.8	266.3	314.7	317.6	2204.0
Luxembourg	10.6	11.8	10.8	11.1	11.0	12.6	12.2	13.8	13.7	15.8	123.4
Netherlands	81.7	78.4	91.4	94.5	86.6	73.6	65.1	63.4	67.7	80.3	782.7
Norway	26.7	32.2	27.8	25.4	30.8	26.8	27.9	31.4	37.4	53.5	319.9
Portugal	6.5	10.5	15.9	151.4	72.0	31.8	34.1	28.1	22.5	32.6	405.4
Spain	57.2	99.1	330.9	394.0	443.1	429.5	645.8	682.7	803.0	920.5	4805.8
Sweden	35.7	34.6	42.6	44.1	47.6	48.0	47.6	51.3	80.4	99.5	531.4
Switzerland	74.9	85.8	87.4	101.4	101.9	94.0	96.3	94.4	102.7	139.7	978.5
United States	653.2	644.8	841.0	1058.9	1059.4	703.5	957.9	1122.4	1266.3	1052.4	9359.8
Total inflow	2397.4	2705.7	3190.3	3662.4	3791.1	3324.3	3803.8	3975.4	4246.0	4421.8	35518.2

Table 2.6: Yearly immigrant flows from our sample of advanced origin countries (thousands)

Destination	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	Total
Australia	41.9	43.4	47.3	54.6	46.5	47.5	58.8	65.0	72.2	76.9	554.1
Austria	8.1	9.2	9.3	12.5	10.3	12.4	15.2	17.2	18.4	20.3	132.9
Belgium	30.3	31.5	32.9	33.0	33.2	33.4	35.8	38.1	40.7	41.6	350.5
Czech Republic	2.5	2.0	1.2	2.7	14.5	25.4	17.0	12.9	9.4	17.5	105.1
Denmark	7.8	7.3	7.4	7.4	7.2	7.3	7.8	8.2	9.8	9.8	80.0
Finland	1.4	1.3	1.3	1.4	1.3	1.4	1.5	1.6	1.7	1.9	14.8
Germany	182.7	188.2	187.6	179.5	168.4	152.2	148.0	143.3	148.3	150.7	1648.9
Hungary	2.5	2.9	3.3	2.9	2.4	2.7	1.6	9.0	4.1	3.0	34.4
Italy	6.1	7.8	9.0	9.2	13.2	11.8	10.3	8.0	6.1	5.1	86.7
Japan	51.6	54.8	55.3	52.0	51.0	50.0	50.4	51.1	53.5	56.7	526.4
Korea	17.3	19.6	21.9	24.2	27.5	24.4	25.4	27.4	27.2	28.8	243.7
Luxembourg	7.9	8.2	8.5	8.7	8.4	9.3	9.0	9.9	10.3	11.1	91.3
Netherlands	27.0	27.7	29.9	30.2	28.3	25.7	24.7	24.8	29.0	31.1	278.4
Norway	15.9	12.7	11.4	11.5	11.4	9.9	10.0	10.6	12.9	16.6	122.9
Portugal	2.9	4.3	4.4	4.9	4.3	3.9	4.0	3.5	2.4	9.9	44.5
Spain	24.2	35.3	45.6	55.7	72.4	76.6	99.0	109.8	124.3	133.0	775.9
Sweden	9.9	11.1	13.7	14.5	15.4	15.2	14.6	14.9	17.7	16.5	143.5
Switzerland	39.2	44.2	47.2	50.3	54.1	53.9	59.3	60.1	66.7	98.0	573.0
United States	66.5	58.9	89.0	119.6	107.2	66.7	95.8	124.3	113.3	96.8	938.1
Total inflow	479.2	511.5	537.2	555.2	569.8	563.0	592.4	615.4	654.7	728.5	5807.0
% of total inflow	19.99	18.90	16.84	15.16	15.03	16.94	15.57	15.48	15.42	16.48	16.35

Note: *% of total inflow* denotes the share of yearly immigrant flows from advanced origin countries covered in total yearly immigrant flows in the destination countries.

Table 2.7: Yearly immigrant flows from our sample of developing origin countries (thousands)

Destination	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	Total
Australia	44.1	48.2	54.3	64.3	63.9	69.4	81.1	87.7	92.8	104.2	710.0
Austria	20.3	24.3	23.5	28.8	28.0	29.7	32.7	31.2	25.1	29.7	273.3
Belgium	12.2	13.3	15.5	21.4	24.4	23.2	24.4	26.2	29.7	37.5	227.8
Czech Republic	3.9	3.5	2.3	7.0	22.9	25.3	27.2	37.0	46.5	67.4	243
Denmark	9.4	9.0	10.7	13.0	10.1	7.6	6.6	6.6	7.6	7.7	88.3
Finland	4.8	4.1	4.6	5.7	5.3	4.8	5.7	6.5	7.1	8.9	57.5
Germany	268.5	298.5	329.9	359.0	357.5	329.7	342.2	337.1	320.3	341.3	3284
Hungary	10.5	12.9	13.4	14.4	13.4	13.9	17.8	12.5	12.0	13.1	133.9
Italy	80.8	176.2	184.3	163.8	252.1	235.2	224.0	139.2	124.0	217.8	1797.4
Japan	144.3	160.9	215.3	223.1	219.4	243.3	243.0	232.8	196.4	202.5	2081
Korea	9.3	8.6	7.9	7.2	10.0	9.3	5.2	10.3	6.8	5.2	79.8
Netherlands	29.2	25.4	27.1	30.1	31.4	32.2	29.0	28.7	29.9	37.9	300.9
Norway	9.8	11.7	13.9	11.5	16.5	14.2	13.7	16.6	20.5	31.9	160.3
Portugal	2.3	4.3	8.4	53.2	29.6	14.6	20.8	16.1	11.9	12.4	173.6
Spain	31.7	60.7	276.5	328.2	364.2	347.9	366.3	451.4	530.9	642.9	3400.7
Sweden	16.7	15.1	17.5	17.9	20.7	20.3	19.3	19.9	37.8	42.1	227.3
Switzerland	3.9	4.7	4.5	5.3	5.3	4.6	4.4	4.1	4.7	4.7	46.2
United States	527.7	529.8	676.1	833.7	838.9	571.2	773.9	875.1	1014.0	850.4	7490.8
Total inflow	1229.4	1411.2	1885.7	2187.6	2313.6	1996.4	2237.3	2339.0	2518.0	2657.6	20775.8
% of total inflow	51.28	52.16	59.11	59.73	61.03	60.05	58.82	58.84	59.30	60.10	58.49

Note: *% of total inflow* denotes the share of yearly immigrant flows from developing origin countries covered in total yearly immigrant flows in the destination countries.

Table 2.8: Descriptive statistics

	Advanced origin countries				Developing origin countries			
Variable	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
$\ln M_{dot}$	6.82	1.49	4.61	10.70	7.06	1.77	4.61	12.30
$\ln MST_{dot}$	9.79	1.71	5.80	14.14	1.00	1.83	5.58	16.46
$\ln M_{dot-1}$	6.78	1.48	4.61	10.70	6.97	1.76	4.61	12.30
$\ln w_{dt-1}$	10.27	0.31	9.22	11.29	10.25	0.25	9.22	10.84
$\ln w_{ot-1}$	10.17	0.28	9.19	11.29	8.41	0.84	5.66	10.89
$\ln ps_{dt-1}$	2.08	0.18	0.75	2.41	2.07	0.15	0.75	2.33
$\ln e_{dt-1}$	4.04	0.12	3.74	4.20	4.04	0.12	3.74	4.20
$\ln e_{ot-1}$	4.02	0.11	3.74	4.31	4.00	0.19	3.41	4.45
$\ln \Delta w_{dt}$	0.05	0.02	-0.01	0.16	0.05	0.02	-0.01	0.16
$\ln \Delta w_{ot}$	0.05	0.02	-0.07	0.16	0.06	0.07	-0.50	0.59
$\ln \Delta ps_{dt}$	0.01	0.04	-0.11	0.25	0.01	0.03	-0.11	0.25
$\ln \Delta e_{dt}$	0.00	0.01	-0.02	0.05	0.01	0.01	-0.02	0.05
$\ln \Delta e_{ot}$	0.00	0.01	-0.04	0.05	0.00	0.03	-0.15	0.22

Note: *Advanced:* 2223 observations, 247 cross sections. *Developing:* 3492 observations, 388 cross sections.

Table 2.9: GMM estimation results

Dependent variable: $\ln M_{dot}$ — Sample period: 1998-2007

	Advanced origins				Developing origins			
	GMMd1	GMMd2	GMMs1	GMMs2	GMMd1	GMMd2	GMMs1	GMMs2
$\ln MST_{dot}$	1.57^{***}	1.08^{**}	0.44^{***}	0.34^{***}	-0.01	-0.10	0.92^{***}	0.94^{***}
	(4.56)	(2.44)	(8.35)	(3.12)	(-0.09)	(-0.46)	(43.26)	(22.37)
$\ln M_{dot-1}$	0.98^{***}	1.01^{***}	0.51^{***}	0.60^{***}	8.39^{***}	8.57	-0.07	0.08
	(7.46)	(5.36)	(10.76)	(5.74)	(4.75)	(1.49)	(-0.51)	(0.33)
$\ln w_{dt-1}$	-2.52^{**}	-1.52	-0.36^{**}	-0.23	0.42	0.31	0.12^{**}	0.09
	(-2.44)	(-1.01)	(-2.22)	(-1.14)	(1.05)	(0.28)	(2.45)	(1.08)
$\ln w_{ot-1}$	0.99	0.59	0.00	-0.02	4.68^{***}	4.53	-0.17	-0.54^{**}
	(0.84)	(0.40)	(-0.01)	(-0.08)	(2.91)	(0.76)	(-1.36)	(-2.49)
$\ln ps_{dt-1}$	-1.09	0.79	-0.03	-0.48^{**}	9.55^{***}	10.57^{**}	-0.27	-0.16
	(-0.57)	(0.32)	(-0.26)	(-2.15)	(4.32)	(2.21)	(-1.26)	(-0.41)
$\ln e_{dt-1}$	-1.33	-2.12	0.17	0.51	15.45^{***}	16.67^{**}	0.25	0.06
	(-1.21)	(-1.61)	(0.55)	(1.08)	(4.33)	(2.00)	(1.51)	(0.22)
$\ln e_{ot-1}$	2.80^{*}	1.69	0.50^{**}	0.21	-1.36	-1.68	1.16^{**}	1.03
	(1.84)	(0.85)	(2.32)	(0.43)	(-1.27)	(-0.77)	(2.48)	(1.40)
$\ln\Delta w_{dt}$	2.39^{***}	2.18^{**}	0.88^{*}	0.33	0.34^{*}	0.31	0.08	0.04
	(2.83)	(2.27)	(1.79)	(0.67)	(1.67)	(0.92)	(0.87)	(0.27)
$\ln\Delta w_{ot}$	-1.28	-0.20	-0.73^{*}	-0.22	-1.27^{*}	-1.19	-0.13	-0.34
	(-1.31)	(-0.17)	(-1.71)	(-0.52)	(-1.77)	(-0.93)	(-0.39)	(-0.65)
$\ln\Delta ps_{dt}$	0.55	0.03	0.71^{**}	0.49	-0.63	-0.82	5.35^{***}	4.49^{***}
	(0.69)	(0.03)	(2.05)	(1.43)	(-0.27)	(-0.19)	(5.29)	(2.85)
$\ln\Delta e_{dt}$	3.52^{**}	2.96^{**}	1.33	0.90	1.12^{**}	0.95	0.07	-0.22
	(2.48)	(2.20)	(1.18)	(1.33)	(2.15)	(0.96)	(0.23)	(-0.41)
$\ln\Delta e_{ot}$	-2.98	-1.83	0.35	-0.01	-0.16^{**}	-0.15	0.07^{***}	0.06^{*}
	(-1.60)	(-0.76)	(0.36)	(-0.01)	(-2.37)	(-0.57)	(3.08)	(1.70)
Sargan and Hansen tests of overidentying restrictions								
χ^2	2.28	2.05	13.65	43.93	3.68	3.77	33.36	90.73
p-value	0.52	0.56	0.55	0.00	0.30	0.29	0.00	0.00

Notes: Each regression includes time dummies (not reported). t-statistics - between brackets - are robust to cross-sectional heteroskedasticity. For the two-step GMM estimators they are calculated from Windmeijer (2005) standard errors. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively. *Advanced:* 2223 observations and 247 cross sections. *Developing:* 3492 observations and 388 cross sections.

The following estimators are reported: (i) GMMd1 and GMMd2, the stacked one-step and two-step versions of the first-differenced GMM estimator proposed by Arellano and Bond (1991) and (ii) GMMs1 and GMMs2, the stacked one-step and two-step versions of the system GMM estimator proposed by Arellano and Bover (1995) and Blundell and Bond (1998). One-step GMM estimators report the Sargan test of overidentifying restrictions; two-step variants report the robust Hansen test. The instrument sets for GMMd and GMMs are exactly the same as the ones used in the Monte Carlo simulation in section 2.2.5.

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3

Determinants of Intraregional Migration in Sub-Saharan Africa 1980-2000[1]

[1]This chapter is the result of joint work with Prof. dr. Glenn Rayp.

Abstract

Despite great accomplishments in the migration literature, the determinants of South-South migration remain poorly understood. In an attempt to fill this gap, this chapter formulates and tests an empirical model for intraregional migration in Sub-Saharan Africa within an extended human capital framework, taking into account spatial interaction. Using bilateral panel data between 1980-2000, we find that intraregional migration on the subcontinent is predominantly driven by economic opportunities and sociopolitics in the host country, facilitated by geographical proximity. The role played by network effects and environmental conditions is also apparent. Finally, origin and destination spatial dependence should definitely not be ignored.

JEL Classification: F22, O15, C23

Keywords: International migration, Sub-Saharan Africa, Spatial interaction, Spatial Durbin model

3.1 Introduction

The motivations for international migration have received a great deal of attention in migration research since the 1980s. The main focus of theoretical and empirical research has been on the principal channels of mass migration in the twentieth century. These include both North-North migration, such as European migration to North America or Australia, as well as South-North migration, such as migration from former colonies to Europe and migration in the context of guest worker programs and exile. Recent empirical studies have typically analyzed migration to Europe (Gallardo-Sejas et al., 2006; Hooghe et al., 2008) or to the OECD (Pedersen et al., 2008; Ortega and Peri, 2009, 2011; Mayda, 2010; Beine et al., 2011; Ruyssen et al., forthcoming), estimating a variant of the human capital model of migration with particular attention to economic determinants.

The driving forces behind migration to developing countries, especially South-South migration, remain poorly understood. Yet, the extent of migration in the South should definitely not be underestimated. The World Bank estimated that in 2000, 51 percent of worldwide migration could be classified as migration to the South[2]. This implies that in 2000, 85 million out of 165 million migrants on the globe were living in a developing country. In Sub-Saharan Africa (SSA), the extent of South-South migration goes even beyond that of South-North migration, with as much as 69 percent of the movement classified as South-South migration. The share of migration to other developing regions (interregional migration) is negligible, suggesting a great deal of intraregional migration on the African subcontinent.[3] The relatively little scholarly attention that international migration

[2]We follow Özden et al. (2011) who classify Australia, Canada, Japan, New Zealand, the United States, the EU-15 and the European Free Trade Association as developed countries, the remaining countries being classified as developing.

[3]For a detailed overview of migratory patterns in SSA see Adepoju (1995), Adebusoye (2006) and Ncube et al. (2010).

within Africa south of the Sahara has received can primarily be linked to the lack of reliable data. Despite great improvements in the availability of international migration data during recent years, detailed long-term data on immigrant flows remain unavailable or incomplete for many developing countries. This is especially the case for the relatively poorer African countries, for which keeping track of border crossings has not been a priority on the policy agenda.

Because data on international SSA migration is scarce, most of the literature dealing with migration in SSA has focused on rural-urban migratory movements within countries (Agesa and Agesa, 1999; Andersson, 2001; de Haan et al., 2002; Hampshire, 2002). Barkley and McMillan (1994), for instance, estimated a migration decision model incorporating both economic conditions as well as political institutions, using panel World Bank data for 32 African countries during 1972-1987. They found support for their hypothesis that the presence of political freedom and civil liberties augments the responsiveness of labor migration to economic incentives. Alternatively, Barrios et al. (2006) analyzed the impact of environmental change on urbanization in SSA using a panel of 78 countries between 1960-1990. They confirmed that, contrary to the results for other developing regions, shortages in rainfall have acted to increase rural-urban movements in SSA countries.

Studies that analyze intraregional SSA migration, on the other hand, typically focus on migration to the south and the west, and mainly involve case studies such as mine migration in South-Africa (Lucas, 1985, 1987; Taylor, 1990), war-related border crossing between Zimbabwe and Mozambique (Hughes, 1999) or Mozambican refugee flows to Malawi (Koser, 1997). To our knowledge, only a few studies have tried to empirically investigate the determinants of intraregional SSA migration on a more comprehensive level. Hatton and Williamson (2002), for instance, estimated the determinants of net out-migration rates (calculated as a residual from demographic accounting) in countries across SSA. They found that Africans are especially driven by wage gaps and demographic booms in the sending country. However, as the authors had no information about the migrants' origin or destination, these results only offer an indication of the motivations for emigration from developing countries, but not necessarily for South-South migration.

The recently constructed Global Bilateral Migration Database (GBMD) described in Özden et al. (2011), however, offers new opportunities to exploit bilateral panel data to investigate incentives for South-South migration as is usually done in a South-North context. Spanning the period 1960-2000, it is the most comprehensive and consistent database on bilateral South-South migration available at present. The database provides statistics on migrant stocks for each decade during this period. The change in migrant stocks between subsequent time periods can then be used as a measure of net migration flows (see also Beine et al., 2011; Marchiori et al., 2012). This approximation is not perfect as it does not take into account deaths and return migration during the 10 years between observation points. Yet, following Beine et al. (2011), we believe that it is accurate enough to provide a reasonable approximation for net migration.

As such, the first contribution of this chapter concerns the use of bilateral panel data to evaluate the factors affecting migration between SSA countries. We specify a comprehensive human capital model of migration that encompasses not only the typical economic determinants of migration but also demographic, sociopolitical and environmental factors representing characteristics of countries of origin and destination as well as network effects and natural and cultural factors enhancing or restraining migrant flows to the host country, such as transport, communication and psychological costs of migration. The model is estimated using data from the GBMD, for 42 origin and destination countries between 1980-1990 and

1990-2000.

The second contribution of this chapter relates to our estimation approach, which takes into account potential spatial interaction between origin-destination (OD) flows. As argued by Griffith and Jones (1980), OD flows from a certain origin (to a certain destination) are positively correlated with the degree of emissiveness (attractiveness) of its neighboring origin (destination) locations. Although several authors have pointed out the need to account for spatial dependence in the analysis of migratory movements (see for example Cushing and Poot, 2003), the use of spatial regression methods in the migration literature is still limited. To address this apparent gap in the literature, LeSage and Pace (2008) develop a family of spatial OD models using a combination of three spatial connectivity matrices for destination, origin and destination-to-origin dependence which can be estimated using maximum-likelihood techniques. We follow this approach, which allows for a general structure of the spatial correlation in the migrant flow. Starting from a spatial Durbin model, the most general model of spatial dependence, we rely on specification tests to determine which model best describes the data.

Our main results can be summarized as follows. Although we find evidence for a strong influence of average incomes in the host country, the role played by sociopolitical factors is also apparent, though only indirectly. The occurrence of conflict in the home country encourages emigration towards countries where relative freedom is secured. These migratory streams are perpetuated because of network effects lowering the psychological costs of migration. Also distance and adjacency play a significant role because of their influence on transport and communication costs. It is shown that the influence of environmental factors should not be underestimated: immigration is higher towards countries with lower disaster occurrence and indirectly also temperature anomalies. Finally, we find indications of significant destination- and origin-based spatial dependence in migration decisions.

The remainder of the chapter is organized as follows. Section 3.2 outlines the empirical model. Section 3.3 describes the data. The introduction of spatial dependence and the estimation method are discussed in Section 3.4. Section 3.5 elaborates on the estimation results and Section 3.6 concludes.

3.2 Empirical model specification

As most of the recent economic literature on the migration decision (see Hatton, 1995; Pedersen et al., 2008; Mayda, 2010; Ruyssen et al., forthcoming), our empirical model is based on Sjaastad's (1962) human capital model of migration. Economic theory suggests that individuals maximize their utility subject to a budget constraint. Accordingly, Sjaastad (1962) argues that the migration decision is based on the comparison between expected benefits and costs from migration. Potential migrants repeat this exercise for each potential destination country and choose the country that provides the best opportunities. The expected benefits and costs from migration depend on many factors related to the characteristics of the individual, the individual's origin country and those of all potential destination countries. In line with Zavodny (1997), Pedersen et al. (2008) and Mayda (2010), we write aggregate migration from origin country o to destination country d at time t as a function of destination, origin and destination-origin characteristics capturing the benefits and costs of migration. Specifically, we define the aggregate migration rate as

$$\frac{M_{dot}}{N_{dt}} = \alpha_0 + \alpha_1 B_{dt} - \alpha_2 B_{ot} - \alpha_3 C_{dot} + \varepsilon_{dot} \tag{3.1}$$

$$B_{dt} = \ln(Y_{dt} Z_{dt}) \tag{3.2}$$

$$B_{ot} = \ln(Y_{ot} Z_{ot}) \tag{3.3}$$

where the migrant flow, M_{dot}, is divided by the resident population in the destination country, N_{dt}, to account for scale effects related to the fact that larger countries are able to provide more opportunities to and host more immigrants.[4] B_{dt}, B_{ot} and C_{dot} denote the expected benefits from migrating to destination d, those for staying in the home country o and the expected costs from migration from o to d, respectively. The expected benefits from migration or staying in the home country are a function of average incomes, Y, and the non-monetary returns, Z, while ε_{dot} denotes the error term, which is assumed i.i.d.[5]

Following Todaro (1969) and Harris and Todaro (1970), expected income is defined as the average income (*inc*) times the employment rate (*empl*) to account for the risk of not finding a job upon arrival in the destination country. Yet, in line with Hatton (1995), we assume that expected earnings abroad are subject to more uncertainty than those in the home country.[6] In fact, we do not impose equal

[4] The empirical specification described in equation (3.1) can be formalised as a linear probability model, i.e. a linear approximation to a model describing the probability that an individual i from country o decides to migrate to d at time t. The corresponding linear probability model would be given by

$$\frac{M_{dot}}{N_{dt}} = Prob(m_{idot} = 1) = \alpha_0 + \alpha_1 B_{dt} - \alpha_2 B_{ot} - \alpha_3 C_{dot} + \varepsilon_{dot}.$$

This relationship allows the model to be fitted using simple linear regression techniques. As argued by Caudill (1988) and Angrist and Pischke (2008), a carefully chosen linear model can yield good estimates of marginal effects, despite some of the well-known drawbacks of the linear probability model. Whereas probit or logit models are generally preferred to a linear probability model, the former only prove better estimators when the disturbances are known to be normally or logistically distributed, respectively. Moreover, contrary to probit or logit models, a linear probability model permits estimation of country specific effects and the parameters are directly interpretable (see e.g. Verbeek, 2012).

[5] Section 3.4 demonstrates how we account for potential spatial dependence in the migratory process and how this affects the structure of the error term. As a robustness check, we also control for the presence of unobserved heterogeneity among destination and origin countries. The results are discussed in Section 3.5. There is not much sense in adding a time effect given that our sample is limited to two time periods.

[6] In fact, Hatton (1995) explicitly takes into account uncertainty about employment prospects abroad and expects a higher coefficient for employment in the destination compared to the origin country. The same reasoning could be applied to the coefficients for other variables such as wages or education prospects. Whereas Hatton (1995) assumes that the probability of employment follows a biniomial distribution, we do not assume any specific distribution and do not impose any

coefficients for employment prospects and average incomes at home or abroad. Taking logarithms, we can write expected incomes in the destination and origin countries, respectively, as

$$\ln Y_{dt} = \beta_1 \ln inc_{dt} + \beta_2 \ln empl_{dt} \tag{3.4}$$

$$\ln Y_{ot} = \delta_1 \ln inc_{ot} + \delta_2 \ln empl_{ot}. \tag{3.5}$$

Combining equations (3.1), (3.4) and (3.5) gives

$$\begin{aligned} \frac{M_{dot}}{N_{dt}} &= \alpha_0 + \alpha_1 \beta_1 \ln inc_{dt} - \alpha_2 \delta_1 \ln inc_{ot} \\ &+ \alpha_1 \beta_2 \ln empl_{dt} - \alpha_2 \delta_2 \ln empl_{ot} \\ &+ \alpha_1 \ln Z_{dt} - \alpha_2 \ln Z_{ot} - \alpha_3 C_{dot} + \varepsilon_{dot}. \end{aligned} \tag{3.6}$$

Through the identification of Z_{dt}, Z_{ot} and C_{dot}, this basic human capital model of migration can be elaborated to account for more structural influences of migration. First, a popular proxy for the cost of migration, C_{dot}, is the social network: family and friends already in the host country may lower the psychological cost for newcomers leaving their familiar surroundings, alleviate financial constraints or help finding a job or housing. To capture these network effects, we incorporate the lagged stock of immigrants already present in the host country (MST) (see also Hatton, 1995; Fertig, 2001; Lewer and Van den Berg, 2008; Pedersen et al., 2008). Also the distance between origin and destination country (*dist*) and the presence of a common border (*commbord*) are considered suitable proxies for monetary expenses and non-monetary opportunity costs (such as foregone earnings while traveling and finding a job) incurred by the migrant (Karemera et al., 2000; Gallardo-Sejas et al., 2006; Lewer and Van den Berg, 2008; Pedersen et al., 2008; Mayda, 2010). Other factors expected to lower the costs of migration are the presence of a

restrictions on the coefficients.

common language (*commlang*) and a common colonial past (*commcol*). Cultural similarities in the host and source country are assumed to make adaptation to the new environment easier, which in turn increases the propensity to migrate between these countries (see also Karemera et al., 2000; Gallardo-Sejas et al., 2006; Lewer and Van den Berg, 2008; Pedersen et al., 2008). Furthermore, we also investigate the impact of regional integration (*regint*) on migration. A positive sign might indicate that regional integration succeeds in stimulating the free movement of people whereas a negative sign might point to a substitution relationship between trade and labor. As such, the cost of migration, C_{dot}, is specified as

$$\begin{aligned} C_{dot} &= \varphi_0 + \varphi_1 \ln MST_{dot-1} - \varphi_2 \ln dist_{do} \\ &\quad + \varphi_3 commbord_{do} + \varphi_4 commlang_{do} + \varphi_5 commcol_{do} + \varphi_6 regint_{do} \end{aligned} \tag{3.7}$$

Second, we look more closely into specific characteristics of the origin and destination countries, Z_{dt} and Z_{ot}, which are likely to influence the return to migration and as such also the decision to migrate. Following the standard practice in the literature, the immigrant's income perspectives in the host country are proxied by GDP per capita. Borjas (1989) and Mayda (2010), however, argue that this proxy does not signal the true income opportunities for an immigrant because differences between the GDP per capita in host and source country are affected by differences in skill intensity. To capture this and to control for the effect of skill differences on GDP per capita, we follow Borjas (1989) and Mayda (2010) by adding the mean skill level of the population (*educ*) in the destination and origin country to the model. We expect the first (latter) to have a negative (positive) impact on migration. Next, assume the decision to migrate does not only depend on the current utility difference net of migration costs, but also on the net present value of all future ones. Specifically, the expected returns to migration are discounted over the remaining lifetime and therefore decreasing with age. As such, young people will have more incentive to migrate, because the discounted value of their expected returns is higher due to their longer remaining working life. Following the literature, we control for this effect by incorporating the share of the young population in the origin country ($youngpop$) (see also Hatton and Williamson, 2002; Gallardo-Sejas et al., 2006; Mayda, 2010). Symmetrically, we include the share of the young population in the destination to capture tension in the host country's labor market, which provides an indication of job opportunities for migrants. Migration is expected to be higher the larger (smaller) the share of young people in the origin (destination) country. Finally, we account for the non-monetary return of migration that arises from locational characteristics, such as sociopolitical and environmental circumstances. Obviously, migrants are expected to prefer countries with less conflict ($confl$) and more relative freedom (fr) (Karemera et al., 2000; Hatton and Williamson, 2002; Pedersen et al., 2008). The latter combines measures of civil liberties and political rights. Because the freedom status and its components are all highly correlated, we include only the former. Additionally, extreme conditions caused by (natural) disasters ($disaster$) or weather anomalies ($climate$) have proven to affect especially the poorest and powerless, for whom migration might be one of many coping mechanisms (Barrios et al., 2006). It is expected that people are more (less) likely to move away from (towards) countries affected by disaster and extreme temperature (see Findley, 1994; Ezra and Kiros, 2001). Hence, $\ln Z_{dt}$ and $\ln Z_{ot}$ are specified as

$$\begin{aligned}\ln Z_{dt} &= \gamma_0 + \gamma_1 \ln educ_{dt} - \gamma_2 \ln popyoung_{dt} - \gamma_3 \ln confl_{dt} \\ &\quad + \gamma_4 \ln fr_{dt} - \gamma_5 \ln disaster_{dt} - \gamma_6 \ln climate_{dt} \qquad (3.8)\\ \ln Z_{ot} &= \eta_0 + \eta_1 \ln educ_{ot} + \eta_2 \ln popyoung_{ot} + \eta_3 \ln confl_{ot} \\ &\quad - \eta_4 \ln fr_{ot} + \eta_5 \ln disaster_{ot} + \eta_6 \ln climate_{ot} \qquad (3.9)\end{aligned}$$

Replacing in (3.6) C_{dot}, Z_{dt} and Z_{ot} by their components and regrouping yields a comprehensive empirical specification of the human capital migration model given by

$$
\begin{aligned}
\frac{M_{dot}}{N_{dt}} = {} & (\alpha_0 + \varphi_0 + \alpha_1\gamma_0 + \alpha_2\eta_0) \\
& + \alpha_1\beta_1 \ln inc_{dt} - \alpha_2\delta_1 \ln inc_{ot} + \alpha_1\beta_2 \ln empl_{dt} - \alpha_2\delta_2 \ln empl_{ot} \\
& + \alpha_3\varphi_1 \ln MST_{dot-1} - \alpha_3\varphi_2 \ln dist_{do} + \alpha_3\varphi_3 commbord_{do} \\
& + \alpha_3\varphi_4 commlang_{do} + \alpha_3\varphi_5 commcol_{do} + \alpha_3\varphi_6 regint_{do} \\
& - \alpha_1\gamma_1 \ln educ_{dt} + \alpha_2\eta_1 \ln educ_{ot} \\
& - \alpha_1\gamma_2 \ln popyoung_{dt} + \alpha_2\eta_2 \ln popyoung_{ot} \\
& - \alpha_1\gamma_3 \ln confl_{dt} + \alpha_2\eta_3 \ln confl_{ot} + \alpha_1\gamma_4 \ln fr_{dt} - \alpha_2\eta_4 \ln fr_{ot} \\
& - \alpha_1\gamma_5 \ln disaster_{dt} + \alpha_2\eta_5 \ln disaster_{ot} \\
& - \alpha_1\gamma_6 \ln climate_{dt} + \alpha_2\eta_6 \ln climate_{ot} + \varepsilon_{dot}. \qquad (3.10)
\end{aligned}
$$

Like in Hatton (1995), Pedersen et al. (2008) and Mayda (2010), our model of international migration has a semi-log functional form, which has the important advantage that it allows to explain not only positive, but also zero and even negative migration rates. This point will be relevant for the choice of our estimation method discussed in Section 3.4.

On the whole, the empirical specification accounts for the traditional *economic determinants*, reflecting average incomes through wages and employment opportunities; *network effects*, captured by the stock of immigrants from the same ethnic origin already in the host country; *geographical and cultural proximity*, measured by the distance between the origin and destination country, the presence of a common border, a common language, a common colonial past and a proxy for regional integration; *the demographic situation*, proxied by the level of education and the share of the young population in the total population; *the political situation* through the occurrence of conflict and citizens' relative freedom; and finally *the environmental impact* captured by the incidence of disaster and the severity of temperature anomalies.

3.3 The data

As argued in the introduction, the lack of complete and reliable data has formed a major obstacle for an in-depth analysis of the incentives for South-South migration. In many developing countries, and particularly in SSA, keeping track of migratory streams has not been a major concern. Organizations such as the United Nations and the US Census Bureau provide estimates on long-term international migration in SSA. Yet, these figures do not allow for a South-South analysis since they are not disaggregated by country of origin.

The approach of early studies of immigration between countries as well as studies of internal movements was to define their dependent variable as the number of persons, born in a given place of origin, residing in each of the destination localities at the date of the census. That is, a migrant stock, rather than a flow variable was used. As a result no distinction could be made between recent and earlier migrants or between those who settled directly in the observed destination and those who arrived through a succession of moves. Furthermore, the migrant stock reflects the result of a process taking place over many years, while the explanatory variables are usually measured at one point in time. Consequently, the determinants may not reflect the conditions existent at the time of the actual move (Dunlevy, 1980). The recently constructed GBMD, on the other hand, offers the opportunity to create migration flows in three dimensions (destination, origin and time), which allow for a rigorous analysis of the determinants of South-South migration. It builds on the United Nations Population Division's Global Migration Database, which augments and updates the bilateral migration matrix compiled by the University of Sussex and Ratha and Shaw (2007). The database mostly provides statistics on foreign born wherever possible, and foreign nationals otherwise. Although the migrant stock data is not perfectly comparable across countries, substantial effort has been made to standardize the data and ensure consistent figures for the number of migrants in each of the five census periods. Though migration on the African continent is in part irregular (given ill-defined migration laws and inconsistent border control), it provides a fairly accurate picture of migratory movements during the period (Beine et al., 2011).[7]

Based on this database, we define our dependent variable as the change in bilateral migrant stocks, that is the difference in the number of foreign residents in each country disaggregated by country of origin, for each decade between 1980-2000. The change in migrant stocks is divided by the population in the destination country (in thousands) to control for size effects as described in Section 3.2.

Given that migration between SSA and northern Africa is very small (the World Bank reports not a single SSA migrant in North-Africa and also in the other direction there is little border crossing) and mainly consists of transit migration, we exclude the north African countries from our sample. Furthermore, also Djibouti, Eritrea, Mayotte, Saint Helena, Sao Tome and Principe, Reunion, the Seychelles, Sudan and Western Sahara are dropped because of missing information for certain country characteristics. For the same reason, our sample is limited to the last two decades in the database. Finally, our sample contains statistics on the change in the stock of migrants in 42 destination countries from the same 42 origin countries, between 1980-1990 and 1990-2000.[8]

Appendix 3.7.1 documents detailed information on measurement and data sources

[7]It is worth mentioning that refugees in camps have been excluded from the database to make the distinction between refugee flows and actual migration. For explicit details on how the data on migrant stocks have been collected and harmonized, we refer to Özden et al. (2011).

[8]For an overview of migration stocks and changes by destination and origin, see Tables 3.4 and 3.5.

for the explanatory variables used in the empirical model.[9] The data have been compiled from various international organizations and research institutes like the World Bank, the United Nations and CEPII. As such, our dataset enables us to proxy for all the determinants used in the empirical model described in Section 3.2. As an indicator of the beginning-of-period values of the explanatory variables, we take the average over the 5-year period prior to the start of the corresponding decade unless stated otherwise. As such, we repress potential problems of endogeneity bias and erratic deviance from the trend value. In the same vein, we use lagged values of the migrant stock, that is the observation prior to the corresponding decade for the dependent variable (we cannot take 5-year averages for migrant stocks because the data are available only decennially).

3.4 Spatial dependence and estimation method

A model of bilateral migration, like (3.10), can be considered a ‘spatial interaction model’, i.e. a model that focuses on flows between origins and destinations as described in Sen and Smith (1995). These models typically explain bilateral flows as a function of characteristics of both origin and destination regions as well as the distance between them. Also the gravity model belongs to this family with several applications in the migration literature (Karemera et al., 2000; Ortega and Peri, 2009). Yet, all of the existing models assume independence of observations, which might be problematic in several contexts, and the recognition of the need to account for spatial dependence in analyzing human migration is widespread (Cushing and Poot, 2004; LeSage and Pace, 2008, 2009; Mitze, 2009).

Using distance as an explanatory variable, gravity models do not effectively capture spatial dependence in international flows (Curry, 1972; Griffith, 2007; LeSage and Pace, 2009). In cases where each country might affect its neighbors, this ap-

[9] Summary statistics can be found in Table 3.6.

proach proves inadequate because it ignores the spatial interrelatedness of bilateral flows. The spatial econometrics literature provides both theoretic and econometric motivations for the use of spatial regression models. An example of the former concerns migration regulations, which are difficult to measure in practice because of their qualitative nature and, therefore, often omitted in empirical specifications. They form, however, an important barrier to migration and are likely to be correlated across countries. Governments might, for instance, decide to set in place certain policy measures after having observed those set by neighboring countries. This type of spatial interdependence might be explicitly integrated in the formal specification of the theoretical model. Yet, it might also be motivated from an econometric perspective by looking upon bilateral flows as describing a diffusion process over space with a time lag. This form of spatial dependence typically shows up in cross-sectional models with a spatial lag of the dependent variable. Another important econometric motivation for the use of spatial regressions concerns the presence of omitted latent influences that are spatial in nature, typically leading to a spatial Durbin model (SDM) with spatial lags of both the dependent and explanatory variables (LeSage and Pace, 2009). Again, migration policy appears an obvious candidate given that it is often an omitted latent influence that is both correlated with the explanatory variables and across locations. Especially the second of these econometric motivations is relevant in the context of this chapter.[10]

LeSage and Pace (2009) show that the SDM is less affected by omitted variable bias than a model that ignores spatial dependence. This holds when the omitted variable is truly involved in the data generating process, but also when it is not, its inclusion does not lead to bias in the estimates. Consequently, the authors suggest relying on a model that includes spatial lags of the dependent and explanatory

[10]The first econometric motive is less likely in view of the time span (10 years) over which we consider the migration rates.

variables even if this seems counter to the underlying theory behind our model. Note that we do not a priori impose any spatial dependence in the migrant flow, as this does not immediately follow from current theoretical models motivated by utility considerations. In line with LeSage and Pace (2008, 2009), our starting point is consistent with the human capital model, which posits a non-spatial theoretical relationship underlying migration flows.

In a model of bilateral flows (like international trade or migration), the spatial interaction structure is likely to be more complex compared to standard spatial lag or spatial error models, because it needs to take into account spatial correlation of the flows at both origins and destinations (LeSage and Pace, 2008, 2009). To emphasize the origin-destination (OD) structure of the migration model, rewrite the unrestricted form of equation (3.10) as

$$\frac{M_{dot}}{N_{dt}} = \theta_0 + \theta_1 \ln MST_{dot-1} + X_{dt}\theta_2 + X_{ot}\theta_3 + X_{do}\theta_4 + \varepsilon_{dot} \tag{3.11}$$

where X_{dt} denotes time-varying destination characteristics, X_{ot} time-varying origin characteristics, X_{do} time invariant bilateral characteristics, $\theta_0 = \alpha_0 + \varphi_0 + \alpha_1\gamma_0 + \alpha_2\eta_0$, $\theta_1 = \alpha_3\varphi_1$, $\theta_2 = \alpha_1 (\beta_1\beta_2\gamma_1...\gamma_6)'$, $\theta_3 = \alpha_2 (\delta_1\delta_2\eta_1...\eta_6)'$, $\theta_4 = \alpha_3(\varphi_2...\varphi_6)'$. Subsequently, we add spatial lags for both the dependent and explanatory variables using a combination of three spatial connectivity matrices W_d, W_o and W_w, for destination, origin and destination-to-origin dependence respectively, as suggested by LeSage and Pace (2008, 2009). The spatial weight matrices are row-normalized contiguity matrices of order one, which take a positive value when two countries are neighbors and zero otherwise. This results in the unconstrained SDM model,

$$\begin{aligned}\frac{M_{dot}}{N_{dt}} &= \theta_0 + \rho_d W_d \left(\frac{M_{dot}}{N_{dt}}\right) + \rho_o W_o \left(\frac{M_{dot}}{N_{dt}}\right) + \rho_w W_w \left(\frac{M_{dot}}{N_{dt}}\right) \\ &\quad + \theta_1 \ln MST_{dot-1} + X_{dt}\theta_2 + X_{ot}\theta_3 + X_{do}\theta_4 \\ &\quad + \theta_5 W_w \ln MST_{dot-1} + W_d X_{dt}\theta_6 + W_o X_{ot}\theta_7 + W_w X_{do}\theta_8 + \varepsilon_{dot} \qquad (3.12)\end{aligned}$$

the most general form of spatial dependence. Subsequently, we run a series of Wald tests to determine whether the SDM can be simplified to a spatial lag or a spatial error model.

LeSage and Pace (2008, 2009) propose a maximum likelihood estimator (MLE) to estimate the SDM. In the context of bilateral migration flows, however, it might be argued that a large number of zero flows invalidates the normality assumption needed for maximum likelihood estimation. For our sample of 1880-2000 migration rates, we have zero values in about 33 percent of the observations. One suggestion to address the issue of zero flows is to aggregate the data to larger spatial units or cumulating flows over a longer time period. Our current database however already considers flows at the highest level of aggregation, that is the country level, which are obtained by combining flows over 10 year periods. Moreover, the fact that our dependent variable also takes negative values (for instance in cases where return migration exceeds immigration between two countries) prevents us from using count data methods such as multinomial logit or tobit models, which by definition require non-negative values (see Beine et al., 2011). The semi-log functional form of our empirical model however allows us to explain migration flows, irrespective of their sign.

To account for the non-normality of the migrant rate, we estimate the empirical SDM using a quasi-maximum likelihood estimator (QMLE), which produces consistent estimates, even if the likelihood function is not entirely correct (but the first-order conditions are) (see White, 1982; Verbeek, 2012). The information matrix test developed by White (1982), suggests that the distribution of the QMLE differs from that of the MLE. The small sample distribution of the QMLE can however be obtained in a numerical way by resampling the original data a 1000 times and applying the MLE in each of the constructed samples. By resampling the data within but not between cross-section units, the data resampling procedure aligns with the assumed data generating process of the data. As such, inference is based on the simulated distribution of the QMLE which allows us to calculate robust standard errors and t-statistics.

An alternative methodology suggested by LeSage and Pace (2009) concerns a Markov Chain Monte Carlo (MCMC) approach, which is based on the decomposition of the posterior distribution into a set of conditional distributions for each parameter in the model. Bayesian parameter estimates are then obtained from repeated sample draws from these conditionals. This approach has the advantage that it decomposes a complicated estimation problem into simpler problems without having to carry out numerical integration of the posterior distribution with respect to the parameters as was needed in conventional Baysian methodology. It is however still considered quite controversial given the subjective choice of prior distributions, the lack of an objective principle for choosing a non-informative prior and the potential influence of these choices on the estimation outcome. Moreover, MCMC techniques cannot guarantee that convergence has taken place. To check the robustness of our results, we re-estimated our empirical model using the MCMC approach suggested by LeSage and Pace (2009) and obtained similar results compared to the QML estimates discussed below.[11]

An implication of accounting for spatial dependence is that the estimated param-

[11]The MCMC estimation results for the SDM model can be found in Table 3.10. Direct, indirect and total effects estimates are reported in Tables 3.11, 3.12 and 3.13, respectively. Although QMLE puts more (less) emphasis on the spatial lags of the dependent variable (explanatory variables) compared to MCMC, the estimated direct and total effects are fairly similar across estimation methods.

eters cannot be interpreted as usual in a standard linear regression model. Cross-country interactions prevent the parameter estimates from being interpreted as the simple partial derivatives of the dependent variable with respect to the explanatory variables (see Anselin and Le Gallo, 2006; Kelejian et al., 2006; LeSage and Pace, 2009). Pace and LeSage (2006) and LeSage and Pace (2009) suggest three summary measures of the varying impacts of changes in an explanatory variable across countries:

(i) average direct impact: the impact from changes in the ith observation of variable k on country i, averaged over all countries

(ii) average indirect impact: the effect of changes in the ith observation of variable k on country j ($\neq i$), averaged over all countries, capturing the spillover effects of a change in country i on all other countries

(iii) average total impact: the sum of the previous two, reflecting how changes in a single country potentially influence all observations.

The direct effects correspond the most to the typical regression coefficient interpretation that represents the average response of the dependent variable to independent variables over the sample of observations. The main difference is that the direct effect takes into account feedback effects from changes in country i to country j and back to country i itself. Because they allow for an explicit comparison with parameter estimates from other studies on migration determinants in the literature, we will concentrate primarily on the average direct effects in the discussion of our results, although we will also consider the indirect effects[12] and briefly comment upon the total effects.

[12] Technically, for the kth variable, the average direct (indirect) effect corresponds to the average of the main diagonal (the average of the row sums of the off-diagonal) elements of the matrix $(I-\rho W)^{-1}(I\theta_{i,k}+W\theta_{i,k+4})$ in (3.12).

The various types of effects estimates are calculated using the empirical distribution of the model parameters. The latter is constructed using a large number of simulated parameters drawn from the QML multivariate normal distribution of the parameters as suggested by LeSage and Pace (2009). Using a 1000 simulated draws, we compute means, standard deviation and t-statistics for direct, indirect and total impacts. For technical details on the calculation of these summary measures as well as measures of dispersion for the impact estimates, we refer to LeSage and Pace (2009).

3.5 Estimation results

In what follows, we present estimation results for nine models in which specific categories of variables are added sequentially until the complete model is reached in the final column.[13] As argued above, we perform a number Wald tests to decide whether the SDM model can be simplified to a spatial lag or spatial error model. The latter are rejected in favor of the SDM, suggesting that the most appropriate model is the one that includes spatial lags of both the dependent and the explanatory variables. Table 3.1 displays test statistics and p-values for each of the nine models. Starting from the basic human capital model with economic determinants and network effects and sequentially adding geographical, cultural, demographical, sociopolitical and environmental explanatory variables, we are able to explain nearly 60 percent of the variation in migration streams.[14]

[13]To be able to estimate a panel version of the SDM using three connectivity matrices, we combined the Matlab software for spatial panels provided by Elhorst (2010, 2013) at his website and the spatial econometric modelling of origin-destination flows described in LeSage and Pace (2008, 2009).

[14]The log likelihood function is likely to be misspecified due to the non-normality of the residuals. Therefore, we cannot rely on likelihood ratio tests to determine whether our general model could be simplified to one of the nine more specific models set forth in LeSage and Pace (2008) which impose various restrictions on the parameters for the spatially lagged dependent variable. Yet, considering that the inclusion of insignificant spatial lags will not lead to bias (see above), we prefer to use the most general model 9 in LeSage and Pace (2008) in all of our model specifica-

Based on these test results, all of the nine SDM models are estimated using pooled QML with three sources of spatial dependence. From Table 3.1, we see that both the destination-based and origin-based spatial lags of the dependent variable are statistically significant, with a dominant influence from the latter. The destination-to-origin based spatial lag, on the other hand, appears insignificant. This suggests the presence of both destination and origin spatial dependence in the migration flow between SSA countries during 1980-2000.[15]

Tables 3.2 and 3.3 report the summary measures of the SDM direct and indirect effects for each of the nine models.[16] With a few exceptions, our results are fairly robust across specifications and mostly consistent with the theoretical predictions of the international migration model.

Focussing on the direct effects first, we start by regressing migrant rates on the economic determinants. Regressions I to IV suggest positive (negative) significant direct effects for income in the destination (origin) country, in line with our expectations, but ambiguous effects for employment rates. In fact, the positive significant impact of income in the destination country is the most robust result across specifications. Income in the origin country has a significantly negative direct effect on migration rates in regression I but this effect diminishes in model III when employment rates enter the equation. When introduced separately, employment rates have an insignificant direct effect on migration rates. Yet, the estimated impact of employment in the origin country becomes significantly negative once we control for average income, in line with the predictions of the human capital model.

---

tions.

[15]The remaining parameter estimates together with their simulated t-statistics for these models can be found in Table 3.8. The difference between the parameter estimates and the direct effects estimates is due to feedback effects that arise as a result of impacts passing through neighboring countries and back to the country itself (see LeSage and Pace, 2009).

[16]Given that the estimated total effects are simply the sum of estimated direct and indirect effects, the latter are not reported in the text, but can be found in Table 3.9.

Table 3.1: Spatial Durbin model estimates

Dependent variable: $\ln M_{dot} / \ln N_{dt}$ — Sample period: 1980-2000

	I	II	III	IV	V	VI	VII	VIII	IX
Log likelihood	-10492	-7824	-7519	-7382	-7392	-7338	-8921	-8520	-7125
Corr^2	0.050	0.011	0.077	0.252	0.510	0.525	0.527	0.584	0.664
Adjusted R^2	-0.174	-0.145	-0.011	0.190	0.422	0.434	0.343	0.423	0.583
Wald Spatial Lag	0.734	8.414	8.622	5.294	9.396	8.945	9.089	11.610	19.230
$Prob > \chi^2$	0.693	0.015	0.071	0.381	0.402	0.537	0.825	0.867	0.631
Wald Spatial Error	3.065	6.998	4.225	3.099	7.801	7.545	8.125	12.007	19.415
$Prob > \chi^2$	0.216	0.030	0.376	0.685	0.554	0.673	0.883	0.847	0.620
$W_d M_{dot}$	0.012***	0.016***	0.017***	0.017***	0.017***	0.017***	0.017***	0.007**	0.018***
	(3.259)	(4.106)	(4.734)	(4.498)	(4.678)	(4.497)	(4.398)	(1.983)	(4.587)
$W_o M_{dot}$	0.285***	0.239***	0.185***	0.182***	0.182***	0.181***	0.263***	0.233***	0.158***
	(7.387)	(6.473)	(4.893)	(4.746)	(4.827)	(4.743)	(7.161)	(6.242)	(4.348)
$W_w M_{dot}$	-0.017	0.009	0.025	0.026	0.025	0.026	0.010	-0.035	0.032
	(-0.747)	(0.371)	(1.098)	(1.109)	(1.082)	(1.109)	(0.435)	(1.575)	(1.391)

Notes: T-statistics in parenthesis are calculated using simulated standard errors based on 1000 bootstrap samples. *** and ** indicate significance at the 1% and 5% level, respectively. Number of observations: 3444. 'Corr^2' denotes the correlation coefficient between actual and fitted values. 'Adjusted R^2' is the coefficient of determination corrected for the degrees of freedom.

Regression IV introduces the network effect. As expected, we find a positive and highly significant effect of migrant stocks on migration rates. According to the estimates in regression IV, an increase in the lagged bilateral migrant stock by 100 persons on average attracts another 7 persons per 1000 individuals in the destination from the same origin. Though these effects are rather small, they provide some first evidence for the role of network effects in encouraging migratory streams in SSA. Ignoring economic determinants or introducing them separately together with the lagged stock variable does not alter this finding (not reported here). Given that our model includes destination, origin and destination-to-origin dependence, this implies that an increase in migrant stocks between one pair of destination and origin countries not only affects migration rates in the respective destination but also in neighbors to this destination and in neighbors to the coun-

Table 3.2: Direct effects estimates

Dependent variable: $\ln M_{dot}/\ln N_{dt}$ Sample period: 1980-2000

Variable	I	II	III	IV	V	VI	VII	VIII	IX
$\ln inc_{dt}$	0.102^{***}		0.163^{***}	0.154^{***}	0.201^{***}	0.212^{***}	0.240^{***}	0.253^{***}	0.242^{***}
	(2.893)		(3.109)	(3.064)	(3.475)	(3.677)	(3.278)	(3.359)	(3.300)
$\ln inc_{ot}$	-0.095^{***}		-0.070^{**}	-0.043	-0.011	0.000	0.004	0.001	-0.012
	(-3.015)		(-2.154)	(-1.338)	(-0.296)	(-0.007)	(0.087)	(0.024)	(-0.277)
$\ln empl_{dt}$		-0.041	-0.004	-0.051	0.071	0.070	0.037	0.021	0.030
		(-0.463)	(-0.033)	(-0.468)	(0.622)	(0.551)	(0.354)	(0.222)	(0.244)
$\ln empl_{ot}$		0.011	-0.192^{***}	-0.214^{**}	-0.141	-0.132	-0.144	-0.160^{*}	-0.095
		(0.116)	(-2.072)	(-2.173)	(-1.340)	(-1.270)	(-1.591)	(-1.735)	(-0.758)
$\ln MST_{dot-1}$				0.069^{***}	0.018	0.023^{*}	0.024	0.027^{*}	0.032^{**}
				(3.367)	(1.575)	(1.776)	(1.636)	(1.799)	(2.241)
$\ln educs_{dt}$							-0.068	-0.082^{*}	-0.131^{**}
							(-1.449)	(-1.750)	(-2.024)
$\ln educs_{ot}$							-0.011	-0.018	-0.022
							(-0.253)	(-0.282)	(-0.355)
$\ln youngpop_{dt}$							-0.050	-0.083	0.062
							(-0.163)	(-0.284)	(0.238)
$\ln youngpop_{ot}$							0.119	0.215	-0.001
							(0.294)	(0.489)	(-0.004)
$\ln confl_{dt}$								0.020	0.243
								(0.148)	(1.528)
$\ln confl_{ot}$								0.205	0.212
								(1.271)	(1.374)
$\ln fr_{dt}$								0.000	0.078
								(0.000)	(0.400)
$\ln fr_{ot}$								0.102	0.127
								(0.695)	(0.883)
$\ln disaster_{dt}$									-0.033^{*}
									(-1.931)
$\ln disaster_{ot}$									-0.012
									(-1.639)
$\ln climate_{dt}$									0.114
									(0.288)
$\ln climate_{ot}$									-0.117
									(-0.787)
$\ln distance_{do}$					-0.154^{*}	-0.174^{*}	-0.183	-0.204	-0.193
					(-1.672)	(-1.848)	(-1.467)	(-1.499)	(-1.400)
$commbord_{do}$					0.607^{**}	0.602^{**}	0.593^{**}	0.573^{**}	0.551^{**}
					(2.271)	(2.266)	(2.326)	(2.209)	(1.995)
$commcol_{do}$					-0.001	0.014	0.015	0.017	0.034
					(-0.009)	(0.137)	(0.136)	(0.139)	(0.296)
$commlang_{do}$					0.076	0.051	0.073	0.058	0.038
					(0.879)	(0.579)	(0.737)	(0.692)	(0.518)
$regint_{do}$						-0.150	-0.153	-0.183^{*}	-0.184
						(-1.452)	(-1.414)	(-1.667)	(-1.490)

T-statistics in parenthesis are calculated using simulated standard errors based on 1000 bootstrap samples. *** and ** indicate significance at the 1% and 5% level, respectively. Number of observations: 3444.

tries where the migration flows originate. The same reasoning can be applied to spillover effects arising from changes in the other explanatory variables.

In the subsequent regressions, we explore the role played by geographical and cultural proximity. It becomes immediately clear that both distance and especially the presence of a common border are fairly important and robust factors for explaining migration rates across specifications (see also Karemera et al., 2000; Mayda, 2010, for the effect of distance). In line with our expectations, migration rates decrease with distance (significantly across all models when we would apply a one-sided test) and are higher when two countries share a common land border. The impact of past colonial relationships appears statistically insignificant. The same holds for the presence of a common language suggesting that, when we control for the other variables included in the regression, cultural proximity does not appear to affect migration rates (see also Mayda, 2010). It should be noted that controlling for geographical and cultural proximity slightly alters the picture. First, it removes the statistically significant direct effect of employment in the origin country from regression IV. Second, it reduces the estimated parameter and significance of the network effect. To be more precise, the direct coefficients for the migrant stock show a substantial drop when we control for bilateral effects but then gradually recover once also demographics, sociopolitical characteristics and especially environmental factors are taken into account.

Regression VI introduces regional integration in the estimation equation. Although we find unambiguous negative direct effects across specifications, the estimated impact is only marginally significant in model VII. As such, we do not find evidence for a positive influence of regional integration on migration through the enhancement of free movement, nor for a negative influence linked to substitution between trade and labor as discussed above.

Next, we introduce the demographic variables. We find that the migration rate

Table 3.3: Indirect effects estimates

Dependent variable: $\ln M_{dot}/\ln N_{dt}$ — Sample period: 1980-2000

Variable	I	II	III	IV	V	VI	VII	VIII	IX
$\ln inc_{dt}$	0.002		−0.043	−0.051	0.020	0.034	0.080	0.070	0.001
	(0.293)		(−1.361)	(−1.387)	(0.282)	(0.484)	(0.777)	(0.596)	(0.009)
$\ln inc_{ot}$	−0.028		−0.041	−0.022	0.015	0.028	0.039	0.000	−0.040
	(−1.586)		(−0.643)	(−0.398)	(0.340)	(0.591)	(0.300)	(0.002)	(−0.297)
$\ln empl_{dt}$		0.022**	0.109*	0.035	0.342*	0.322	0.069	0.333	0.674**
		(2.216)	(1.681)	(0.505)	(1.671)	(1.570)	(0.307)	(1.500)	(2.091)
$\ln empl_{ot}$		0.052*	0.042	0.013	−0.029	−0.046	0.214	0.139	0.019
		(1.644)	(0.367)	(0.121)	(−0.319)	(−0.473)	(1.094)	(0.750)	(0.108)
$\ln MST_{dot-1}$				0.083	0.010	0.010	0.013	0.033	0.065
				(1.201)	(0.260)	(0.248)	(0.277)	(0.577)	(0.985)
$\ln educs_{dt}$							−0.104	−0.154	−0.253
							(−0.884)	(−0.897)	(−1.292)
$\ln educs_{ot}$							0.067	0.106	0.065
							(0.479)	(0.690)	(0.491)
$\ln youngpop_{dt}$							0.286	0.038	−0.040
							(0.607)	(0.093)	(−0.085)
$\ln youngpop_{ot}$							−0.327	−0.202	−0.198
							(−1.243)	(−0.751)	(−0.926)
$\ln confl_{dt}$								−0.301	0.037
								(−0.910)	(0.117)
$\ln confl_{ot}$								0.632*	0.626*
								(1.698)	(1.733)
$\ln fr_{dt}$								0.562	0.792**
								(1.550)	(2.163)
$\ln fr_{ot}$								0.050	0.193
								(0.331)	(1.111)
$\ln disaster_{dt}$									−0.071***
									(−2.829)
$\ln disaster_{ot}$									−0.025
									(−1.196)
$\ln climate_{dt}$									−0.467
									(−0.947)
$\ln climate_{ot}$									0.505
									(1.401)
$\ln distance_{do}$					−0.202	−0.201	−0.205	−0.188	−0.212
					(−1.397)	(−1.357)	(−1.218)	(−1.204)	(−1.312)
$commbord_{do}$					1.249	1.214	1.151	0.919	0.946
					(1.565)	(1.568)	(1.475)	(1.373)	(1.370)
$commcol_{do}$					0.073	0.051	−0.016	−0.064	−0.051
					(0.214)	(0.149)	(−0.053)	(−0.249)	(−0.186)
$commlang_{do}$					−0.112	−0.069	−0.064	−0.121	−0.228
					(−0.367)	(−0.231)	(−0.204)	(−0.385)	(−0.628)
$regint_{do}$						−0.159	−0.155	−0.241	−0.300
						(−0.762)	(−0.684)	(−0.968)	(−1.199)

T-statistics in parenthesis are calculated using simulated standard errors based on 1000 bootstrap samples. *** and ** indicate significance at the 1% and 5% level, respectively. Number of observations: 3444.

is negatively related to the level of secondary education in the destination. This supports the argument of Borjas (1989) and Mayda (2010) for the necessity to correct for the effect of skill differences on the proxies for the immigrant's income perspectives, at least in the destination country. The schooling level in the origin country, on the other hand remains insignificant (in line with Mayda, 2010). As far as concerns the share of the young population, though generally of the right sign, we find insignificant effects. As such, we cannot confirm that intraregional migration in Sub-Saharan Africa responds to fluctuations in employment due to demographic pressure, or that the incentive to migrate significantly decreases with age.

In regressions VIII and IX we investigate to what extent migration rates are shaped by the sociopolitical characteristics of origin and destination countries. We find no evidence of an important role played by these factors (except for the occurrence of conflict in the source country in a one-sided test).

Finally, regression IX combines all regressors described above and investigates the relative importance of environmental factors in explaining the migration rate. According to our estimations, the number of people affected by disaster relative to the population in the host country has a significantly negative direct effect on migration. Hence, the destination choice of immigrants is influenced by the occurrence of (natural) disaster. Our evidence suggests insignificant coefficients for the remaining direct effects after controlling for other aspects of the migration decision. Robustness checks using more specific proxies for the environmental impact, such as the relative number of people affected by natural disasters (drought, earthquake, epidemic, extreme temperature, flood, insect infestation, mass movement, storm, volcano or wildfire) or climatic disasters in particular (drought, extreme temperature or wildfire), and even using the number of people affected by these type of disasters in absolute terms do not alter these results. It should however be mentioned that the impact of natural disasters depends on the socio-economic situation of the people affected and, more specifically, on their adaptation mechanisms which improve their ability to cope with extreme climatic events (Meze-Hausken, 2000; Haug, 2002). Our variable capturing climate change, measured by temperature anomalies, appears insignificant. These results are robust to whether disaster and temperature anomalies enter the regression together or one at a time (not reported).[17]

As far as concerns the indirect effects, the estimates suggest that only a limited number of spillover effects are significant. First of all, the indirect effects of income per capita in the home and destination country are fairly small and always insignificant. In some models, we find significant positive spillover effects for employment rates in the destination country (in the model including only employment rates and the complete model IX), but this result is not robust. Hence, the economic determinants of migration (and migrant networks) only have a direct impact on international migration. For conflict at the origin country, however, we find a positive significant indirect impact, pointing to a regional dimension of conflict: the occurrence of wars in neighboring countries seems to incite people to leave their home country. In the last model, we also find evidence for a positive impact of relative freedom (in terms of civil liberties and political rights) in the broader destination area (in line with Barkley and McMillan, 1994), just as the occurrence of disaster in this area indirectly discourages migration towards the countries in that region. Therefore, apart for the economic determinants, we find

[17] We note that other studies have also used precipitation in their analysis of the impact of weather anomalies on migration rates. Adding rain anomalies would however imply a reduction in the sample size, which made us decide not to use it in our empirical analysis. Rainfall and temperature both drive evapotranspiration, suggesting that they might be considered alternative measures of the same event. Though different samples place different emphasis on the relative importance of rainfall or temperature, they find robust evidence for an impact from weather anomalies on migration (see e.g. Barrios et al., 2006; Marchiori et al., 2012). Others argue that crop growth and thus the impact of weather on agriculture income variability stems solely from temperature anomalies and should be measured accordingly (see e.g. Burke et al., 2009; Dillon et al., 2011).

evidence for the presence of spillover effects (and hence a regional dimension) only for the sociopolitical and environmental determinants in our model.

As mentioned above, the total effects are calculated as the sum of the direct and indirect effects. Given that for most variables, the latter remain fairly limited, the total effects estimates are generally very similar to those obtained for the direct effects (for instance for income per capita in the destination or origin country). An exception concerns the sociopolitical and environmental variables, for which the indirect effects significantly reinforce the direct effects, such that the total effects are substantially stronger than the latter.

Robustness checks

Next, we verify the robustness of our results for potential measurement error and unobserved heterogeneity. First, in case of measurement error, our results would be biased downward. In order to get an idea of potential measurement errors, we can exploit the time dimension of our data. Assuming that the problem of measurement error is the most serious for the oldest data (considering the efforts by international institutions in collecting data on developing countries in the recent decades), we re-estimated our model for each period separately (that is for migration flows between 1980-1990 and between 1990-2000, respectively), as a first robustness check. For the first period, we find relatively more coefficient estimates insignificantly different from zero compared to the panel data estimations. This is in line with what we would expect from measurement error. However, for the second period, we find significant coefficients of the same sign and results that are very similar to those obtained for the panel model. Because the estimations using only the more accurate data confirm the results of the overall estimation, we believe that the influence of measurement error in the reported results remains fairly mild.

Second, we re-estimate our model with destination and origin specific effects to test for the presence of unobserved heterogeneity. A number of Wald tests indicate that, for the most complete model, the hypotheses of jointly significant country specific effects can be rejected at the 1 percent significance level.[18] This suggests that there is no remaining unobserved heterogeneity once all categories of migration determinants as well as spatial interaction have been taken into account.

3.6 Conclusions

Despite great accomplishments in the migration literature, little is still known about the determinants of South-South migration. In an attempt to fill this gap, we examine what has been driving intraregional migration in SSA, using the World Bank's Global Bilateral Migration Database. We estimate the determinants of migration rates between 42 origin and destination countries for the period 1980-2000, taking into account spatial dependence in the migration decision.

Our theoretical framework is based on Sjaastad's (1962) human capital model of migration and encompasses economic variables as well as network effects, geographical and cultural proximity, demographics, the sociopolitical landscape and the environmental impact. This comprehensive model allows us to evaluate the relative importance of the different factors driving migration patterns in SSA. In addition, we allow for spatial dependence in the migration rates and their determinants. We find a significant impact of both destination- and origin-based spatial dependence in the migration decision, which confirms the necessity to control for both types of spatial correlation when estimating a bilateral model of migration. Once we take into account spatial dependence in both the dependent and the ex-

[18]The test statistics for destination, origin and combined effects, were 52.13, 36.50 and 16.91, respectively.

planatory variables, specification tests reveal that our model shows no remaining unobserved heterogeneity.

Our evidence suggests that SSA migration results from a multidimensional set of factors. The results seem to confirm the hypothesis of Ratha and Shaw (2007) that South-South migration is to a large extent driven by income differences, networks and geographical proximity. On the other hand, we also find support for the role played by conflicts in the home country and relative freedom in the host country. Furthermore, deteriorating environmental conditions in a specific country discourage migration towards it. While for the economic determinants and migrant networks, the direct effects seem to dominate, our results suggest the presence of spillover effects (and hence a regional dimension) for the sociopolitical and environmental determinants.

As such, our results are in line with the main findings of the literature on South-South migration determinants, as discussed for instance in Bakewell (2009), for which we provide empirical evidence. Caution in generalizing these results to other contexts of South-South migration remains necessary, as the South combines a largely heterogeneous mixture of countries with idiosyncratic profiles and region specific developments. Yet, it should be clear that an analysis of migration in a South-South context should include economic determinants as well as other determinants that match the specificities of the particular setting.

3.7 Appendix

3.7.1 Data sources

Migration data

- Migrant stocks ($\ln MST_{dot-1}$): the number of foreign residents in each destination in 1970 and 1980, disaggregated by country of origin. To avoid taking the log of zero, we add unity to each observation. *Source*: World Bank GBMD.

- Migrant rates (M_{dot}/N_{dt}): proxied by the change in MST_{dot} between 1980-1990 and 1990-2000 per 1000 of the average destination country's population. *Source*: World Bank GBMD and US Census Bureau's Population Estimates.

Explanatory variables

- Incomes ($\ln inc$): due to the lack of real wage data, average incomes are approximated by the log of gross domestic product per capita in purchasing power parities at 2005 constant prices. *Source*: Penn World Tables 7.0.

- Employment rates ($\ln empl$): log of the ratio of employed persons to the entire population. *Source*: compiled from the ILO's Key Indicators of the Labor Market, the Total Economy Database and the UN's Labor Force Statistics.

- Education ($\ln educ$): log of enrollment in secondary education divided by the population of the age group that typically corresponds to this level of education. *Source*: UNESCO Institute for Statistics.

- Share of the young population ($\ln youngpop$): log of the population aged between 0 and 14 as a percentage of the total population. *Source*: Africa Development Indicators (2010).

- Conflict ($\ln confl$): dichotomous variable capturing whether multiple regional wars took place during the decade. *Source*: Africa Migration Project's Violence and Unrest Variables.

- Disaster ($\ln disaster$): log of the share of the population affected (injured and deaths) by disasters such as droughts, earthquakes, epidemics, etc. (decade totals). *Source*: Emergency Events Database.

- Climate ($\ln clim$): log of temperature deviations from the century average (decade averages). *Source*: Intergovernmental Panel on Climate Change.

- Relative freedom ($\ln fr$): categorical variable which takes the values free, partly free and not free and reflects a combination of measures on civil liberties and political rights (decennium averages). In particular, political rights represent the degree of implementation or non-implementation of a country's democratic processes. Civil liberties reflect civil rights and desires in education, freedom of religion and choice of residence. *Source*: Freedom House.

- Distance ($\ln dist$): log of distance between the main cities (in population terms) of origin and destination countries. *Source*: CEPII Distance Database (2010).

- Contiguity (*commbord*), colonial ties (*commcol*) and common language (*commlang*): dichotomous variables coded 1 if origin and destination countries share respectively a common border, a former colonizer, or a common ethnological language (a language that is spoken by at least 9 percent of the population in both countries) and 0 otherwise. *Source*: CEPII Distance Database (2010).

- Regional economic integration (*regint*): dichotomous variable coded 1 if both countries were or became a member of the same regional economic community during the decade under consideration, and 0 otherwise. The regional economic communities taken into account are ECOWAS, ECCAS, IGAD and SADC.

Table 3.4: Migration stocks and changes by destination

	Migrant stocks			Migrant stock change		Migrant stock change/ Population$_d$*1000	
Destination	1980	1990	2000	1980-1990	1990-2000	1980-1990	1990-2000
Angola	7673	8426	13272	753	4846	0.104	0.511
Benin	55397	72877	125159	17480	52282	5.055	11.111
Botswana	1553	16547	41429	14994	24882	16.651	19.676
Burkina Faso	87135	153914	149175	66779	-4739	10.569	-0.567
Burundi	78283	64388	51640	-13895	-12748	-3.233	-2.303
Cameroon	145513	197749	166486	52236	-31263	5.961	-2.631
Cape Verde	5546	3283	3815	-2263	532	-7.634	1.566
Central African Republic	46327	54163	16943	7836	-37220	3.336	-12.065
Chad	54194	59896	67871	5702	7975	1.261	1.365
Comoros	13902	12073	11825	-1829	-248	-5.383	-0.576
Congo, Democratic Republic	182604	126189	103313	-56415	-22876	-1.945	-0.584
Congo, Republic	68643	113912	21023	45269	-92889	27.038	-40.992
Equatorial Guinea	3341	1736	2866	-1605	1130	-6.269	3.045
Ethiopia	143927	151311	159060	7384	7749	0.205	0.16
Gabon	63476	116867	177840	53391	60973	74.795	64.997
Gambia	71963	112565	162529	40602	49964	62.229	52.537
Ghana	55525	96175	136824	40650	40649	3.692	2.638
Guinea	18662	75214	238929	56552	163715	12.716	26.758
Guinea-Bissau	12507	11546	11094	-961	-452	-1.218	-0.454
Kenya	91953	100050	489530	8097	389480	0.496	16.672
Lesotho	3597	3066	3924	-531	858	-0.391	0.504
Liberia	69842	69842	66437	0	-3405	0	-1.592
Madagascar	3155	9163	8278	6008	-885	0.691	-0.076
Malawi	283745	278751	273844	-4994	-4907	-0.798	-0.514
Mali	99705	97873	78225	-1832	-19648	-0.269	-2.36
Mauritania	29193	50284	55570	21091	5286	13.652	2.746
Mauritius	1671	1082	2680	-589	1598	-0.611	1.505
Mozambique	11214	79249	294579	68035	215330	5.622	16.578
Namibia	61072	97899	93733	36827	-4166	34.807	-2.833
Niger	70811	112483	156589	41672	44106	6.839	5.625
Nigeria	1010988	367636	616421	-643352	248785	-8.598	2.573
Rwanda	38447	43482	346505	5035	303023	0.98	43.293
Senegal	96860	180641	178114	83781	-2527	14.931	-0.344
Sierra Leone	87765	86387	87498	-1378	1111	-0.413	0.263
Somalia	10721	15285	15688	4564	403	0.788	0.06
South Africa	534447	916630	708724	382183	-207906	13.065	-5.403
Swaziland	27998	30004	33841	2006	3837	3.281	4.352
Tanzania	381619	295308	229336	-86311	-65972	-4.624	-2.616
Togo	132878	138798	143000	5920	4202	2.255	1.129
Uganda	477926	315123	240689	-162803	-74434	-13.114	-4.264
Zambia	195614	129824	117469	-65790	-12355	-11.659	-1.572
Zimbabwe	395848	373347	343378	-22501	-29969	-3.138	-2.951

Table 3.5: Migration stocks and changes by origin

	Migrant stocks			Migrant stock change		Migrant stock change/ Population$_d$*1000	
Destination	1980	1990	2000	1980-1990	1990-2000	1980-1990	1990-2000
Angola	80893	106562	109996	25669	3434	3.562	0.362
Benin	338087	206629	283809	-131458	77180	-38.015	16.402
Botswana	77211	71831	33345	-5380	-38486	-5.975	-30.433
Burkina Faso	98499	103114	120524	4615	17410	0.73	2.082
Burundi	266845	176588	149908	-90257	-26680	-20.999	-4.82
Cameroon	107246	74011	91552	-33235	17541	-3.793	1.476
Cape Verde	12374	12689	29803	315	17114	1.063	50.371
Central African Republic	30319	23298	17078	-7021	-6220	-2.989	-2.016
Chad	105600	139195	111939	33595	-27256	7.429	-4.666
Comoros	5883	13099	12981	7216	-118	21.239	-0.274
Congo, Democratic Republic	227587	244635	493524	17048	248889	0.588	6.357
Congo, Republic	24900	27005	39873	2105	12868	1.257	5.679
Equatorial Guinea	21854	31832	45731	9978	13899	38.975	37.454
Ethiopia	7061	8957	22895	1896	13938	0.053	0.288
Gabon	4014	4554	10198	540	5644	0.756	6.017
Gambia	16881	16859	16466	-22	-393	-0.034	-0.413
Ghana	276337	177951	224906	-98386	46955	-8.935	3.047
Guinea	219223	270879	251557	51656	-19322	11.615	-3.158
Guinea-Bissau	42044	59574	64005	17530	4431	22.221	4.449
Kenya	159459	96745	99833	-62714	3088	-3.84	0.132
Lesotho	215510	324547	171044	109037	-153503	80.258	-90.123
Liberia	29077	54128	157105	25051	102977	13.489	48.152
Madagascar	17350	15665	16030	-1685	365	-0.194	0.031
Malawi	249004	255780	213695	6776	-42085	1.083	-4.409
Mali	259250	209038	302577	-50212	93539	-7.361	11.233
Mauritania	55426	69903	75008	14477	5105	9.371	2.652
Mauritius	11131	14341	10187	3210	-4154	3.331	-3.913
Mozambique	395272	458518	565895	63246	107377	5.226	8.267
Namibia	64565	104499	57694	39934	-46805	37.744	-31.828
Niger	156895	99767	153531	-57128	53764	-9.375	6.856
Nigeria	211522	221861	231364	10339	9503	0.138	0.098
Rwanda	333590	277895	162916	-55695	-114979	-10.836	-16.427
Senegal	126078	166829	201451	40751	34622	7.262	4.712
Sierra Leone	22460	45179	115148	22719	69969	6.812	16.548
Somalia	100049	103345	144118	3296	40773	0.569	6.093
South Africa	107432	146279	264060	38847	117781	1.328	3.061
Swaziland	45525	71912	44058	26387	-27854	43.154	-31.595
Tanzania	143025	123466	153438	-19559	29972	-1.048	1.189
Togo	182107	130980	185378	-51127	54398	-19.473	14.62
Uganda	79510	78675	393485	-835	314810	-0.067	18.035
Zambia	115442	142056	121640	26614	-20416	4.716	-2.598
Zimbabwe	190703	260368	275400	69665	15032	9.716	1.48

Table 3.6: Summary statistics

Variable	Obs	Mean	S.D.	Min	Max
M_{dot}/N_{dt}	3444	0.130	1.670	-26.868	42.879
$\ln inc_{dt}$	3444	6.985	0.785	5.445	9.477
$\ln inc_{ot}$	3444	3.893	0.288	2.989	4.481
$\ln empl_{dt}$	3444	3.232	0.749	1.389	4.671
$\ln empl_{ot}$	3444	3.809	0.071	3.423	3.909
$\ln MST_{dot-1}$	3444	3.203	3.211	0.000	12.566
$\ln educs_{dt}$	3444	0.080	0.196	0.000	0.693
$\ln educs_{ot}$	3444	0.297	0.361	0.000	1.099
$\ln youngpop_{dt}$	3444	0.252	0.336	0.000	1.553
$\ln youngpop_{ot}$	3444	1.157	0.237	0.713	1.493
$\ln confl_{dt}$	3444	6.985	0.785	5.445	9.477
$\ln confl_{ot}$	3444	3.893	0.288	2.989	4.481
$\ln fr_{dt}$	3444	3.232	0.749	1.389	4.671
$\ln fr_{ot}$	3444	3.809	0.071	3.423	3.909
$\ln disaster_{dt}$	3444	0.297	0.361	0.000	1.099
$\ln disaster_{ot}$	3444	0.751	0.314	0.000	1.099
$\ln climate_{dt}$	3444	0.252	0.336	0.000	1.553
$\ln climate_{ot}$	3444	1.157	0.237	0.713	1.493
$\ln distance_{do}$	3444	7.925	0.760	2.349	9.178
$commbord_{do}$	3444	0.085	0.279	0.000	1.000
$commcol_{do}$	3444	0.254	0.436	0.000	1.000
$commlang_{do}$	3444	0.310	0.463	0.000	1.000
$regint_{do}$	3444	0.230	0.424	0.000	2.000
$W_d \ln inc_{dt}$	3444	6.549	1.879	0.000	8.717
$W_o \ln inc_{ot}$	3444	3.617	1.016	0.000	4.194
$W_d \ln empl_{dt}$	3444	2.999	0.937	0.000	4.671
$W_o \ln empl_{ot}$	3444	3.544	0.984	0.000	3.874
$W_w \ln MST_{dot-1}$	3444	3.119	1.450	0.000	12.002
$W_d \ln educs_{dt}$	3444	0.077	0.137	0.000	0.693
$W_o \ln educs_{ot}$	3444	0.272	0.200	0.000	0.749
$W_d \ln youngpop_{dt}$	3444	0.221	0.204	0.000	0.914
$W_o \ln youngpop_{ot}$	3444	1.070	0.340	0.000	1.425
$W_d \ln confl_{dt}$	3444	6.484	1.845	0.000	9.477
$W_o \ln confl_{ot}$	3444	3.615	1.021	0.000	4.481
$W_d \ln fr_{dt}$	3444	3.001	0.923	0.000	4.671
$W_o \ln fr_{ot}$	3444	3.537	0.982	0.000	3.909
$W_d \ln disaster_{dt}$	3444	0.276	0.208	0.000	1.099
$W_o \ln disaster_{ot}$	3444	0.699	0.262	0.000	1.099
$W_d \ln climate_{dt}$	3444	0.234	0.193	0.000	1.553
$W_o \ln climate_{ot}$	3444	1.075	0.324	0.000	1.493
$W_w \ln distance_{do}$	3444	7.315	2.105	0.000	8.991
$W_w commbord_{do}$	3444	0.094	0.104	0.000	1.000
$W_w commcol_{do}$	3444	0.244	0.165	0.000	1.000
$W_w commlang_{do}$	3444	0.306	0.188	0.000	1.000
$W_w regint_{do}$	3444	0.224	0.149	0.000	1.000

Note: The sample includes 42 destination and origin countries.

Table 3.7: Correlation coefficients

		1	2	3	4	5	6	7	8	9	10	11
1	$\ln inc_{dt}$	1.000										
2	$\ln inc_{ot}$	-0.024	1.000									
3	$\ln empl_{dt}$	-0.314^{***}	0.003	1.000								
4	$\ln empl_{ot}$	0.003	-0.314^{***}	0.225^{***}	1.000							
5	$\ln MST_{dot-1}$	-0.023	-0.088^{***}	0.058^{***}	0.069^{***}	1.000						
6	$\ln educs_{dt}$	0.598^{***}	-0.015	-0.238^{***}	0.042^{**}	0.026	1.000					
7	$\ln educs_{ot}$	-0.015	0.598^{***}	0.042^{**}	-0.238^{***}	-0.105^{***}	-0.019	1.000				
8	$\ln youngpop_{dt}$	-0.376^{***}	0.009	0.127^{***}	0.016	0.042^{**}	-0.173^{***}	0.007	1.000			
9	$\ln youngpop_{ot}$	0.009	-0.376^{***}	0.016	0.127^{***}	0.081^{***}	0.007	-0.173^{***}	-0.023	1.000		
10	$\ln confl_{dt}$	-0.135^{***}	0.004	0.186^{***}	-0.016	0.022	-0.227^{***}	0.004	0.041^{**}	-0.002	1.000	
11	$\ln confl_{ot}$	0.004	-0.135^{***}	-0.016	0.186^{***}	-0.031^{*}	0.004	-0.227^{***}	-0.002	0.041^{**}	-0.024	1.000
12	$\ln fr_{dt}$	0.340^{***}	-0.008	-0.144^{***}	-0.014	-0.027	0.448^{***}	-0.013	-0.172^{***}	0.003	-0.165^{***}	0.005
13	$\ln fr_{ot}$	-0.008	0.340^{***}	-0.014	-0.144^{***}	-0.101^{***}	-0.013	0.448^{***}	0.003	-0.172^{***}	0.005	-0.165^{***}
14	$\ln disaster_{dt}$	-0.262^{***}	0.006	0.107^{***}	0.032^{*}	0.016	-0.247^{***}	0.011	0.333^{***}	-0.006	0.199^{***}	-0.006
15	$\ln disaster_{ot}$	0.006	-0.262^{***}	0.032^{*}	0.107^{***}	0.013	0.011	-0.247^{***}	-0.006	0.333^{***}	-0.006	0.199^{***}
16	$\ln climate_{dt}$	-0.007	0.000	0.333^{***}	-0.002	0.024	-0.010	0.001	-0.276^{***}	0.007	0.082^{***}	-0.002
17	$\ln climate_{ot}$	0.000	-0.007	-0.002	0.333^{***}	-0.012	0.001	-0.010	0.007	-0.276^{***}	-0.002	0.082^{***}
18	$\ln distance_{do}$	0.021	0.021	-0.083^{***}	-0.083^{***}	-0.553^{***}	0.000	0.000	-0.102^{***}	-0.102^{***}	0.016	0.016
19	$commbord_{do}$	0.015	0.015	-0.015	-0.015	0.214^{***}	0.011	0.011	0.011	0.011	-0.118^{***}	-0.118^{***}
20	$commcol_{do}$	0.111^{***}	0.111^{***}	0.048^{***}	0.048^{***}	0.169^{***}	0.157^{***}	0.157^{***}	-0.069^{***}	-0.069^{***}	-0.126^{***}	-0.126^{***}
21	$commlang_{do}$	-0.010	-0.010	0.027	0.027	0.557^{***}	-0.036^{**}	-0.036^{**}	0.043^{**}	0.043^{**}	0.008	0.008
22	$regint_{do}$	0.049^{***}	0.049^{***}	-0.027	-0.027	0.467^{***}	0.038^{**}	0.038^{**}	-0.040^{**}	-0.040^{**}	-0.004	-0.004

		12	13	14	15	16	17	18	19	20	21	22
12	$\ln fr_{dt}$	1.000										
13	$\ln fr_{ot}$	-0.023	1.000									
14	$\ln disaster_{dt}$	0.150^{***}	-0.006	1.000								
15	$\ln disaster_{ot}$	-0.006	0.150^{***}	-0.020	1.000							
16	$\ln climate_{dt}$	-0.168^{***}	0.004	-0.354^{***}	0.009	1.000						
17	$\ln climate_{ot}$	0.004	-0.168^{***}	0.009	-0.354^{***}	-0.024	1.000					
18	$\ln distance_{do}$	0.126^{***}	0.126^{***}	0.079^{***}	0.079^{***}	-0.046^{***}	-0.046^{***}	1.000				
19	$commbord_{do}$	0.067^{***}	0.067^{***}	0.063^{***}	0.063^{***}	-0.041^{*}	-0.041^{**}	-0.097^{***}	1.000			
20	$commcol_{do}$	0.155^{***}	0.155^{***}	-0.056^{***}	-0.056^{***}	0.075^{***}	0.075^{***}	-0.085^{***}	0.410^{***}	1.000		
21	$commlang_{do}$	-0.033^{*}	-0.033^{*}	-0.003	-0.003	-0.016	-0.016	-0.387^{***}	0.138^{***}	0.130^{***}	1.000	
22	$regint_{do}$	0.045^{***}	0.045^{***}	0.009	0.009	-0.055^{***}	-0.055^{***}	-0.516^{***}	0.092^{***}	0.045^{***}	0.366^{***}	1.000

Note: *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Table 3.8: Spatial Durbin model estimates

Dependent variable: $\ln M_{dot}/\ln N_{dt}$									Sample period: 1980-2000
Variable	I	II	III	IV	V	VI	VII	VIII	IX
$\ln inc_{dt}$	0.101^{***}		0.163^{***}	0.156^{***}	0.202^{***}	0.213^{***}	0.240^{***}	0.256^{***}	0.243^{***}
	(2.804)		(3.142)	(3.074)	(3.619)	(3.582)	(3.212)	(3.410)	(3.329)
$\ln inc_{ot}$	-0.093^{***}		-0.067^{**}	−0.043	−0.013	−0.001	0.004	0.000	−0.012
	(−2.907)		(−2.074)	(−1.357)	(−0.358)	(−0.021)	(0.072)	(0.008)	(−0.257)
$\ln empl_{dt}$		−0.040	−0.005	−0.051	0.060	0.071	0.035	0.019	0.029
		(−0.448)	(−0.044)	(−0.462)	(0.534)	(0.558)	(0.336)	(0.185)	(0.239)
$\ln empl_{ot}$		0.007	-0.194^{**}	-0.218^{**}	−0.140	−0.130	-0.152^{*}	-0.170^{*}	−0.094
		(0.076)	(−2.052)	(−2.197)	(−1.375)	(−1.273)	(−1.671)	(−1.750)	(−0.731)
$\ln MST_{dot-1}$				0.069^{***}	0.018	0.023^{*}	0.024^{*}	0.028^{*}	0.032^{**}
				(3.266)	(1.606)	(1.736)	(1.704)	(1.949)	(2.158)
$\ln educs_{dt}$							−0.068	-0.083^{*}	-0.128^{**}
							(−1.401)	(−1.749)	(−1.977)
$\ln educs_{ot}$							−0.015	−0.022	−0.025
							(−0.316)	(−0.312)	(−0.382)
$\ln youngpop_{dt}$							−0.057	−0.088	0.071
							(−0.184)	(−0.304)	(0.283)
$\ln youngpop_{ot}$							0.145	0.225	−0.008
							(0.371)	(0.504)	(−0.030)
$\ln confl_{dt}$								0.025	0.238
								(0.182)	(1.457)
$\ln confl_{ot}$								0.178	0.189
								(1.106)	(1.189)
$\ln fr_{dt}$								−0.005	0.075
								(−0.031)	(0.384)
$\ln fr_{ot}$								0.095	0.120
								(0.634)	(0.810)
$\ln disaster_{dt}$									-0.033^{*}
									(−1.920)
$\ln disaster_{ot}$									−0.012
									(−1.580)
$\ln climate_{dt}$									0.108
									(0.264)
$\ln climate_{ot}$									−0.130
									(−0.838)
$\ln distance_{do}$					-0.149^{*}	-0.178^{*}	−0.187	−0.202	−0.191
					(−1.655)	(−1.870)	(−1.549)	(−1.496)	(−1.347)
$commbord_{do}$					0.600^{**}	0.614^{**}	0.591^{**}	0.565^{**}	0.546^{**}
					(2.227)	(2.296)	(2.213)	(2.131)	(2.054)
$commcol_{do}$					0.007	0.015	0.009	0.021	0.034
					(0.073)	(0.145)	(0.087)	(0.178)	(0.290)
$commlang_{do}$					0.067	0.053	0.073	0.059	0.037
					(0.777)	(0.602)	(0.765)	(0.743)	(0.496)
$regint_{do}$						−0.154	−0.155	−0.185	−0.182
						(−1.482)	(−1.463)	(−1.658)	(−1.530)
$W_d \ln inc_{dt}$	0.000		−0.045	−0.052	0.015	0.030	0.071	0.072	−0.005
	(0.046)		(−1.408)	(−1.408)	(0.220)	(0.430)	(0.689)	(0.610)	(−0.047)
$W_o \ln inc_{ot}$	0.006		−0.025	−0.011	0.019	0.024	0.023	0.001	−0.034
	(0.845)		(−0.465)	(−0.246)	(0.486)	(0.604)	(0.216)	(0.010)	(−0.275)

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Variable	I	II	III	IV	V	VI	VII	VIII	IX
$W_d \ln empl_{dt}$		0.023**	0.108*	0.036	0.338*	0.317	0.060	0.339	0.649**
		(2.266)	(1.694)	(0.537)	(1.683)	(1.563)	(0.270)	(1.503)	(2.059)
$W_o \ln empl_{ot}$		0.040***	0.077	0.052	−0.006	−0.015	0.208	0.151	0.033
		(2.826)	(0.772)	(0.588)	(−0.081)	(−0.193)	(1.296)	(0.968)	(0.199)
$W_w \ln MST_{dot-1}$				0.077	0.005	0.010	0.013	0.036	0.057
				(1.139)	(0.139)	(0.255)	(0.289)	(0.601)	(0.887)
$W_d \ln educs_{dt}$							−0.097	−0.155	−0.243
							(−0.816)	(−0.902)	(−1.243)
$W_o \ln educs_{ot}$							0.060	0.087	0.061
							(0.544)	(0.672)	(0.491)
$W_d \ln youngpop_{dt}$							0.319	0.042	−0.013
							(0.689)	(0.100)	(−0.027)
$W_o \ln youngpop_{ot}$							−0.281	−0.216	−0.171
							(−1.554)	(−1.160)	(−0.888)
$W_d \ln confl_{dt}$								−0.295	0.037
								(−0.934)	(0.119)
$W_o \ln confl_{ot}$								0.450	0.505
								(1.490)	(1.587)
$W_d \ln fr_{dt}$								0.555	0.769**
								(1.522)	(2.157)
$W_o \ln fr_{ot}$								0.021	0.144
								(0.165)	(0.959)
$W_d \ln disaster_{dt}$									−0.069***
									(−2.729)
$W_o \ln disaster_{ot}$									−0.020
									(−1.109)
$W_d \ln climate_{dt}$									−0.443
									(−0.861)
$W_o \ln climate_{ot}$									0.453
									(1.469)
$W_w \ln distance_{do}$					−0.191	−0.192	−0.213	−0.210	−0.206
					(−1.367)	(−1.339)	(−1.299)	(−1.266)	(−1.360)
$W_w commbord_{do}$					1.147	1.207	1.121	0.939	0.872
					(1.516)	(1.590)	(1.496)	(1.401)	(1.291)
$W_w commcol_{do}$					0.043	0.051	−0.006	−0.065	−0.051
					(0.130)	(0.155)	(−0.021)	(−0.243)	(−0.192)
$W_w commlang_{do}$					−0.089	−0.075	−0.065	−0.122	−0.212
					(−0.299)	(−0.250)	(−0.212)	(−0.375)	(−0.583)
$W_w regint_{do}$						−0.158	−0.167	−0.258	−0.285
						(−0.787)	(−0.771)	(−1.010)	(−1.170)
$W_d M_{dot}$	0.012***	0.016***	0.017***	0.017***	0.017***	0.017***	0.017***	0.007**	0.018***
	(3.259)	(4.106)	(4.734)	(4.498)	(4.678)	(4.497)	(4.398)	(1.983)	(4.587)
$W_o M_{dot}$	0.285***	0.239***	0.185***	0.182***	0.182***	0.181***	0.263***	0.233***	0.158***
	(7.387)	(6.473)	(4.893)	(4.746)	(4.827)	(4.743)	(7.161)	(6.242)	(4.348)
$W_w M_{dot}$	−0.017	0.009	0.025	0.026	0.025	0.026	0.010	−0.035	0.032
	(−0.747)	(0.371)	(1.098)	(1.109)	(1.082)	(1.109)	(0.435)	(−1.575)	(1.391)

Notes: T-statistics in parenthesis are calculated using simulated standard errors based on 1000 bootstrap samples. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. Number of observations: 3444.

Table 3.9: Total effects estimates

Dependent variable: $\ln M_{dot}/\ln N_{dt}$									Sample period: 1980-2000
Variable	I	II	III	IV	V	VI	VII	VIII	IX
$\ln inc_{dt}$	0.103∗∗∗		0.120∗∗∗	0.103∗∗	0.221∗∗	0.246∗∗∗	0.320∗∗	0.323∗∗	0.243∗
	(3.020)		(2.837)	(2.036)	(2.422)	(2.691)	(2.259)	(2.077)	(1.672)
$\ln inc_{ot}$	−0.123∗∗∗		−0.111	−0.065	0.005	0.028	0.043	0.001	−0.052
	(−2.653)		(−1.380)	(−0.980)	(0.077)	(0.464)	(0.368)	(0.010)	(−0.411)
$\ln empl_{dt}$		−0.019	0.106	−0.017	0.413∗	0.392	0.107	0.354	0.704∗∗
		(−0.210)	(0.722)	(−0.115)	(1.733)	(1.564)	(0.423)	(1.399)	(1.982)
$\ln empl_{ot}$		0.062	−0.151	−0.202	−0.170	−0.177	0.070	−0.022	−0.075
		(0.526)	(−1.027)	(−1.370)	(−1.046)	(−1.079)	(0.353)	(−0.116)	(−0.411)
$\ln stock_{dot-1}$				0.152∗	0.028	0.034	0.036	0.060	0.097
				(1.804)	(0.700)	(0.762)	(0.803)	(1.029)	(1.395)
$\ln educs_{dt}$							−0.172	−0.236	−0.384
							(−1.269)	(−1.161)	(−1.570)
$\ln educs_{ot}$							0.056	0.087	0.043
							(0.433)	(0.654)	(0.359)
$\ln youngpop_{dt}$							0.237	−0.045	0.022
							(0.458)	(−0.084)	(0.037)
$\ln youngpop_{ot}$							−0.208	0.013	−0.199
							(−0.358)	(0.020)	(−0.582)
$\ln confl_{dt}$								−0.281	0.280
								(−0.777)	(0.822)
$\ln confl_{ot}$								0.837∗∗	0.838∗∗
								(2.179)	(2.224)
$\ln fr_{dt}$								0.562	0.870∗
								(1.097)	(1.657)
$\ln fr_{ot}$								0.152	0.321
								(0.691)	(1.347)
$\ln disaster_{dt}$									−0.105∗∗∗
									(−3.421)
$\ln disaster_{ot}$									−0.037∗
									(−1.730)
$\ln climate_{dt}$									−0.353∗
									(−1.659)
$\ln climate_{ot}$									0.388
									(1.044)
$\ln distance_{do}$					−0.355∗	−0.376∗∗	−0.388	−0.392∗	−0.406∗
					(−1.944)	(−1.963)	(−1.632)	(−1.733)	(−1.688)
$commbord_{do}$					1.856∗	1.816∗	1.745∗	1.492∗	1.497∗
					(1.899)	(1.907)	(1.851)	(1.772)	(1.705)
$commcol_{do}$					0.072	0.065	−0.002	−0.047	−0.017
					(0.243)	(0.221)	(−0.006)	(−0.223)	(−0.072)
$commlang_{do}$					−0.036	−0.019	0.009	−0.063	−0.190
					(−0.130)	(−0.069)	(0.034)	(−0.215)	(−0.557)
$regint_{do}$						−0.308	−0.308	−0.424	−0.484
						(−1.236)	(−1.184)	(−1.421)	(−1.539)

Notes: T-statistics in parenthesis are calculated using simulated standard errors based on 1000 bootstrap samples. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. Number of observations: 3444.

Table 3.10: Spatial Durbin model estimates- MCMC

Dependent variable: $\ln M_{dot} / \ln N_{dt}$ Sample period: 1980-2000

Variable	I	II	III	IV	V	VI	VII	VIII	IX
$\ln inc_{dt}$	0.106***		0.171***	0.162***	0.214***	0.226***	0.258***	0.273***	0.247***
	(3.006)		(3.707)	(3.423)	(4.363)	(4.672)	(3.564)	(3.679)	(3.447)
$\ln inc_{ot}$	−0.099***		−0.071	−0.044	−0.015	0.002	0.012	0.009	−0.006
	(−2.734)		(−1.524)	(−0.976)	(−0.318)	(0.048)	(0.185)	(0.144)	(−0.100)
$\ln empl_{dt}$		−0.036	−0.009	−0.058	0.076	0.082	0.088	0.051	0.057
		(−0.315)	(−0.065)	(−0.449)	(0.582)	(0.594)	(0.540)	(0.303)	(0.311)
$\ln empl_{ot}$		−0.003	−0.203	−0.222	−0.147	−0.133	−0.130	−0.150	−0.091
		(−0.022)	(−1.571)	(−1.610)	(−1.096)	(−0.987)	(−0.847)	(−0.912)	(−0.511)
$\ln MST_{dot-1}$				0.066***	0.013	0.020	0.020	0.025	0.031*
				(5.254)	(0.831)	(1.190)	(1.176)	(1.421)	(1.855)
$\ln educs_{dt}$							−0.060	−0.077	−0.121
							(−0.780)	(−0.972)	(−1.491)
$\ln educs_{ot}$							−0.016	−0.023	−0.026
							(−0.242)	(−0.322)	(−0.363)
$\ln youngpop_{dt}$							−0.160	−0.195	−0.053
							(−0.333)	(−0.386)	(−0.098)
$\ln youngpop_{ot}$							0.129	0.242	0.056
							(0.282)	(0.526)	(0.107)
$\ln confl_{dt}$								0.078	0.264
								(0.329)	(1.076)
$\ln confl_{ot}$								0.187	0.207
								(0.913)	(0.982)
$\ln fr_{dt}$								0.001	0.081
								(0.008)	(0.583)
$\ln fr_{ot}$								0.100	0.136
								(0.782)	(0.997)
$\ln disaster_{dt}$									−0.031*
									(−1.810)
$\ln disaster_{ot}$									−0.013
									(−0.798)
$\ln climate_{dt}$									0.104
									(0.407)
$\ln climate_{ot}$									−0.091
									(−0.458)
$\ln distance_{do}$					−0.161***	−0.170***	−0.195***	−0.214***	−0.198***
					(−2.732)	(−3.082)	(−2.801)	(−2.950)	(−2.762)
$commbord_{do}$					0.613***	0.614***	0.607***	0.565***	0.552***
					(3.425)	(3.447)	(3.447)	(3.132)	(3.077)
$commcol_{do}$					−0.001	0.008	−0.002	0.015	0.035
					(−0.009)	(0.074)	(−0.018)	(0.138)	(0.317)
$commlang_{do}$					0.065	0.050	0.071	0.047	0.024
					(0.658)	(0.522)	(0.694)	(0.461)	(0.236)
$regint_{do}$						−0.174*	−0.171*	−0.206*	−0.192*
						(−1.535)	(−1.461)	(−1.743)	(−1.648)
$W_d \ln inc_{dt}$	0.004		−0.042	−0.056	0.017	0.031	0.041	0.049	−0.021
	(0.189)		(−0.643)	(−0.881)	(0.247)	(0.455)	(0.289)	(0.320)	(−0.139)
$W_o \ln inc_{ot}$	0.010		−0.023	−0.010	0.020	0.026	0.011	−0.011	−0.049
	(0.494)		(−0.365)	(−0.154)	(0.313)	(0.398)	(0.095)	(−0.094)	(−0.405)

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Variable	I	II	III	IV	V	VI	VII	VIII	IX
$W_d \ln empl_{dt}$		0.031	0.109	0.044	0.363**	0.329**	−0.004	0.347	0.670*
		(0.801)	(0.929)	(0.374)	(2.410)	(2.137)	(−0.013)	(0.898)	(1.705)
$W_o \ln empl_{ot}$		0.046	0.079	0.053	−0.004	−0.012	0.182	0.104	−0.008
		(1.154)	(0.686)	(0.459)	(−0.031)	(−0.100)	(0.721)	(0.406)	(−0.027)
$W_w \ln MST_{dot-1}$				0.083**	0.006	0.012	0.016	0.043	0.062
				(2.504)	(0.129)	(0.281)	(0.367)	(0.910)	(1.306)
$W_d \ln educs_{dt}$							−0.071	−0.152	−0.243
							(−0.451)	(−0.879)	(−1.387)
$W_o \ln educs_{ot}$							0.065	0.097	0.056
							(0.534)	(0.752)	(0.408)
$W_d \ln youngpop_{dt}$							0.447	0.094	0.015
							(0.921)	(0.183)	(0.030)
$W_o \ln youngpop_{ot}$							−0.231	−0.146	−0.107
							(−0.673)	(−0.429)	(−0.311)
$W_d \ln confl_{dt}$								−0.358	0.016
								(−1.065)	(0.044)
$W_o \ln confl_{ot}$								0.518	0.543
								(1.368)	(1.453)
$W_d \ln fr_{dt}$								0.630**	0.813**
								(2.307)	(2.531)
$W_o \ln fr_{ot}$								0.013	0.160
								(0.054)	(0.654)
$W_d \ln disaster_{dt}$									−0.074*
									(−1.857)
$W_o \ln disaster_{ot}$									−0.025
									(−0.812)
$W_d \ln climate_{dt}$									−0.476
									(−1.061)
$W_o \ln climate_{ot}$									0.475
									(1.267)
$W_w \ln distance_{do}$					−0.203***	−0.197***	−0.222***	−0.217***	−0.210***
					(−3.092)	(−2.966)	(−3.083)	(−2.981)	(−3.013)
$W_w commbord_{do}$					1.254**	1.316**	1.254**	1.020*	0.975*
					(2.490)	(2.549)	(2.440)	(1.650)	(1.838)
$W_w commcol_{do}$					0.102	0.101	0.052	−0.021	−0.019
					(0.348)	(0.340)	(0.176)	(−0.071)	(−0.063)
$W_w commlang_{do}$					−0.124	−0.106	−0.108	−0.173	−0.248
					(−0.463)	(−0.406)	(−0.414)	(−0.628)	(−0.908)
$W_w regint_{do}$						−0.205	−0.211	−0.307	−0.325
						(−0.597)	(−0.611)	(−0.871)	(−0.925)
$W_d M_{dot}$	0.002	0.000	0.001	0.000	−0.002	−0.001	−0.001	−0.002	−0.002
	(0.130)	(0.030)	(0.055)	(−0.023)	(−0.160)	(−0.046)	(−0.066)	(−0.131)	(−0.138)
$W_o M_{dot}$	−0.001	0.000	−0.001	0	−0.001	−0.002	0	−0.003	−0.003
	(−0.068)	(0.000)	(−0.058)	(−0.001)	(−0.085)	(−0.155)	(−0.037)	(−0.249)	(−0.222)
$W_w M_{dot}$	0.001	0.000	0.000	0.000	0.000	−0.001	0.001	0	−0.001
	(0.111)	(0.071)	(0.044)	(0.056)	(−0.049)	(−0.126)	(0.164)	(−0.022)	(−0.073)

Notes: T-statistics in parenthesis are calculated using simulated standard errors based on 1000 bootstrap samples. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. Number of observations: 3444.

Table 3.11: Direct effects estimates - MCMC

Dependent variable: $\ln M_{dot} / \ln N_{dt}$ Sample period: 1980-2000

Variable	I	II	III	IV	V	VI	VII	VIII	IX
$\ln inc_{dt}$	0.108***	0.000	0.171***	0.162***	0.213***	0.226***	0.252***	0.274***	0.250***
	(2.918)	(0.000)	(3.730)	(3.460)	(4.388)	(4.649)	(3.521)	(3.856)	(3.425)
$\ln inc_{ot}$	−0.100***		−0.070	−0.045	−0.013	0	0.010	0.007	−0.008
	(−2.632)		(−1.491)	(−0.968)	(−0.279)	(0.009)	(0.158)	(0.111)	(−0.123)
$\ln empl_{dt}$		−0.036	−0.006	−0.052	0.072	0.082	0.085	0.054	0.058
		(−0.324)	(−0.047)	(−0.398)	(0.543)	(0.600)	(0.521)	(0.320)	(0.322)
$\ln empl_{ot}$		−0.002	−0.207	−0.227*	−0.149	−0.135	−0.123	−0.148	−0.091
		(−0.020)	(−1.581)	(−1.750)	(−1.122)	(−1.012)	(−0.790)	(−0.912)	(−0.504)
$\ln MST_{dot-1}$				0.067***	0.014	0.020	0.011	0.026	0.030*
				(5.323)	(0.877)	(1.237)	(1.134)	(1.452)	(1.691)
$\ln educs_{dt}$							−0.058	−0.078	−0.122
							(−0.781)	(−1.001)	(−1.526)
$\ln educs_{ot}$							−0.013	−0.020	−0.027
							(−0.192)	(−0.286)	(−0.372)
$\ln youngpop_{dt}$							−0.178	−0.190	−0.050
							(−0.366)	(−0.384)	(−0.094)
$\ln youngpop_{ot}$							0.157	0.228	0.054
							(0.339)	(0.495)	(0.104)
$\ln confl_{dt}$								0.067	0.267
								(0.284)	(1.049)
$\ln confl_{ot}$								0.188	0.205
								(0.911)	(0.942)
$\ln fr_{dt}$								0.002	0.079
								(0.016)	(0.551)
$\ln fr_{ot}$								0.101	0.135
								(0.818)	(0.991)
$\ln disaster_{dt}$									−0.031*
									(−1.787)
$\ln disaster_{ot}$									−0.013
									(−0.805)
$\ln climate_{dt}$									0.110
									(0.425)
$\ln climate_{ot}$									−0.095
									(−0.466)
$\ln distance_{do}$					−0.159***	−0.193***	−0.198***	−0.213***	−0.198***
					(−2.656)	(−3.086)	(−2.770)	(−2.926)	(−2.717)
$commbord_{do}$					0.604***	0.615***	0.600***	0.565***	0.550***
					(3.405)	(3.464)	(3.371)	(3.174)	(3.052)
$commcol_{do}$					−0.001	0.007	0.001	0.017	0.032
					(−0.015)	(0.068)	(0.007)	(0.160)	(0.309)
$commlang_{do}$					0.064	0.050	0.062	0.046	0.027
					(0.671)	(0.531)	(0.622)	(0.454)	(0.268)
$regint_{do}$						−0.171	−0.174	−0.208*	−0.192*
						(−1.504)	(−1.501)	(−1.754)	(−1.661)

Notes: T-statistics in parenthesis. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. Number of observations: 3444.

Table 3.12: Indirect effects estimates - MCMC

Dependent variable: $\ln M_{dot} / \ln N_{dt}$ Sample period: 1980-2000

Variable	I	II	III	IV	V	VI	VII	VIII	IX
$\ln inc_{dt}$	0.003		−0.045	−0.056	0.016	0.030	0.039	0.051	−0.018
	(0.160)		(−0.732)	(−0.886)	(0.233)	(0.447)	(0.272)	(0.346)	(−0.121)
$\ln inc_{ot}$	0.009		−0.024	−0.01	0.021	0.028	0.010	−0.010	−0.046
	(0.441)		(−0.362)	(−0.151)	(0.315)	(0.430)	(0.086)	(−0.089)	(−0.395)
$\ln empl_{dt}$		0.031	0.115	0.044	0.353^{**}	0.329^{**}	0.001	0.338	0.680^{*}
		(0.801)	(0.999)	(0.373)	(2.294)	(2.161)	(0.002)	(0.901)	(1.698)
$\ln empl_{ot}$		0.046	0.080	0.055	−0.004	−0.015	0.163	0.111	−0.007
		(1.169)	(0.667)	(0.449)	(−0.037)	(−0.130)	(0.678)	(0.441)	(−0.022)
$\ln MST_{dot-1}$				0.085^{**}	0.005	0.013	0.016	0.042	0.062
				(2.444)	(0.120)	(0.291)	(0.356)	(0.897)	(1.319)
$\ln educs_{dt}$							−0.069	−0.152	−0.241
							(−0.441)	(−0.897)	(−1.362)
$\ln educs_{ot}$							0.063	0.097	0.058
							(0.511)	(0.741)	(0.427)
$\ln youngpop_{dt}$							0.445	0.1	−0.001
							(0.002)	(0.200)	(−0.002)
$\ln youngpop_{ot}$							−0.204	−0.153	−0.110
							(−0.633)	(−0.452)	(−0.312)
$\ln confl_{dt}$								−0.344	0.017
								(−1.027)	(0.045)
$\ln confl_{ot}$								0.495	0.546
								(1.316)	(1.409)
$\ln fr_{dt}$								0.627^{**}	0.810^{**}
								(2.329)	(2.474)
$\ln fr_{ot}$								0.008	0.154
								(0.034)	(0.631)
$\ln disaster_{dt}$									-0.073^{*}
									(−1.902)
$\ln disaster_{ot}$									−0.024
									(−0.794)
$\ln climate_{dt}$									−0.480
									(−1.070)
$\ln climate_{ot}$									0.473
									(1.273)
$\ln distance_{do}$					-0.160^{***}	-0.196^{***}	-0.222^{***}	-0.219^{***}	-0.211^{***}
					(−2.899)	(−2.937)	(−3.095)	(−2.988)	(−2.909)
$commbord_{do}$					1.269^{**}	1.342^{***}	1.282^{**}	1.029^{*}	0.975^{*}
					(2.483)	(2.635)	(2.446)	(1.931)	(1.827)
$commcol_{do}$					0.090	0.088	0.053	−0.023	−0.018
					(0.303)	(0.299)	(0.176)	(−0.076)	(−0.060)
$commlang_{do}$					−0.126	−0.100	−0.112	−0.157	−0.244
					(−0.477)	(−0.377)	(−0.418)	(−0.583)	(−0.879)
$regint_{do}$						−0.208	−0.215	−0.300	−0.324
						(−0.618)	(−0.616)	(−0.859)	(−0.930)

Notes: T-statistics in parenthesis. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. Number of observations: 3444.

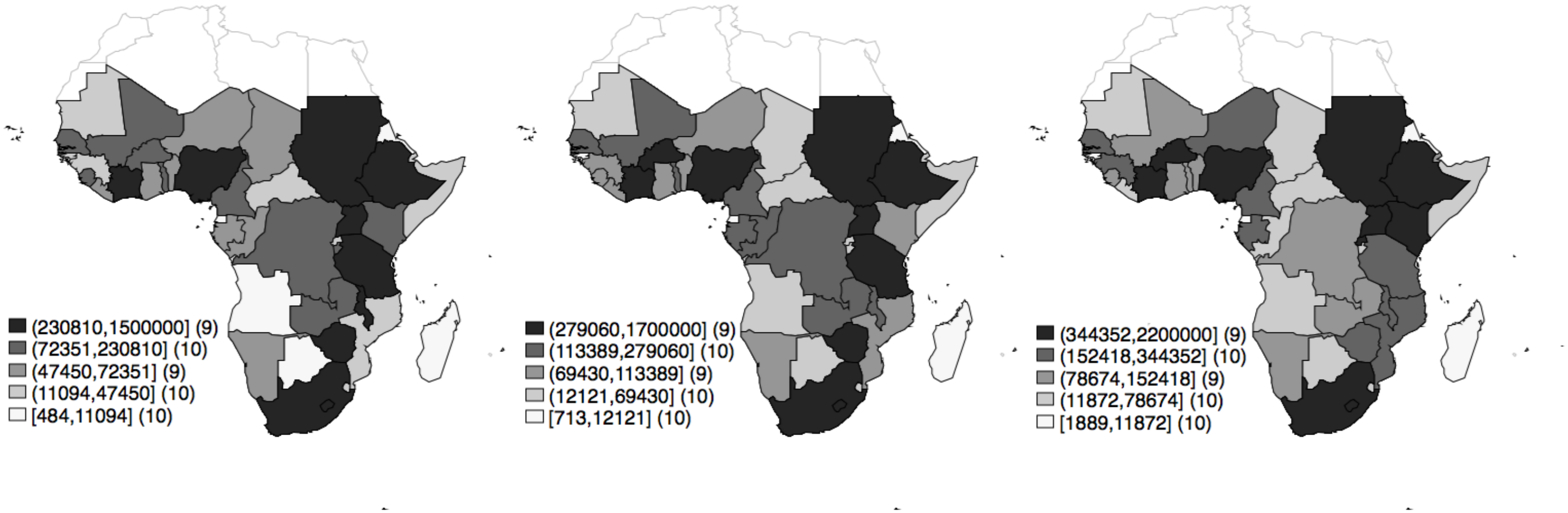
Table 3.13: Total effects estimates - MCMC

Dependent variable: $\ln M_{dot}/\ln N_{dt}$								Sample period: 1980-2000	
Variable	I	II	III	IV	V	VI	VII	VIII	IX
$\ln inc_{dt}$	0.111^{***}		0.126^{*}	0.105	0.228^{***}	0.256^{***}	0.291	0.324^{*}	0.232
	(2.876)		(1.771)	(1.460)	(2.965)	(3.205)	(1.590)	(1.739)	(1.241)
$\ln inc_{ot}$	-0.091^{**}		−0.094	−0.055	0.007	0.029	0.020	−0.003	−0.054
	(−2.346)		(−1.166)	(−0.687)	(0.087)	(0.348)	(0.150)	(−0.024)	(−0.393)
$\ln empl_{dt}$		−0.005	0.108	−0.008	0.425^{**}	0.411^{**}	0.086	0.392	0.738^{*}
		(−0.046)	(0.692)	(−0.052)	(2.314)	(2.236)	(0.246)	(1.042)	(1.777)
$\ln empl_{ot}$		0.044	−0.127	−0.172	−0.154	−0.151	0.040	−0.036	−0.098
		(0.384)	(−0.736)	(−1.005)	(−0.883)	(−0.868)	(0.152)	(−0.133)	(−0.314)
$\ln MST_{dot-1}$				0.151^{***}	0.019	0.033	0.036	0.068	0.092^{*}
				(4.074)	(0.407)	(0.701)	(0.735)	(1.336)	(1.803)
$\ln educs_{dt}$							−0.127	−0.230	-0.363^{*}
							(−0.703)	(−1.178)	(−1.783)
$\ln educs_{ot}$							0.050	0.077	0.031
							(0.347)	(0.509)	(0.132)
$\ln youngpop_{dt}$							0.268	−0.090	−0.051
							(0.416)	(−0.132)	(−0.070)
$\ln youngpop_{ot}$							−0.047	0.075	−0.056
							(−0.085)	(0.132)	(−0.091)
$\ln confl_{dt}$								−0.277	0.284
								(−0.692)	(0.594)
$\ln confl_{ot}$								0.682	0.751^{*}
								(1.572)	(1.681)
$\ln fr_{dt}$								0.629^{**}	0.888^{***}
								(2.288)	(2.608)
$\ln fr_{ot}$								0.108	0.288
								(0.412)	(1.013)
$\ln disaster_{dt}$									-0.104^{***}
									(−2.521)
$\ln disaster_{ot}$									−0.037
									(−1.067)
$\ln climate_{dt}$									−0.370
									(−0.964)
$\ln climate_{ot}$									0.379
									(0.885)
$\ln distance_{do}$					-0.355^{***}	-0.389^{***}	-0.420^{***}	-0.431^{***}	-0.409^{***}
					(−4.161)	(−4.409)	(−4.201)	(−4.222)	(−4.094)
$commbord_{do}$					1.874^{***}	1.664^{***}	1.883^{***}	1.594^{***}	1.525^{***}
					(3.551)	(3.705)	(3.486)	(2.861)	(2.738)
$commcol_{do}$					0.088	0.023	0.053	−0.006	0.014
					(0.283)	(0.305)	(0.167)	(−0.020)	(0.042)
$commlang_{do}$					−0.062	−0.050	−0.042	−0.111	−0.217
					(−0.220)	(−0.178)	(−0.174)	(−0.381)	(−0.731)
$regint_{do}$						−0.379	−0.389	−0.508	−0.516
						(−1.069)	(−1.063)	(−1.380)	(−1.403)

Notes: T-statistics in parenthesis. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. Number of observations: 3444.

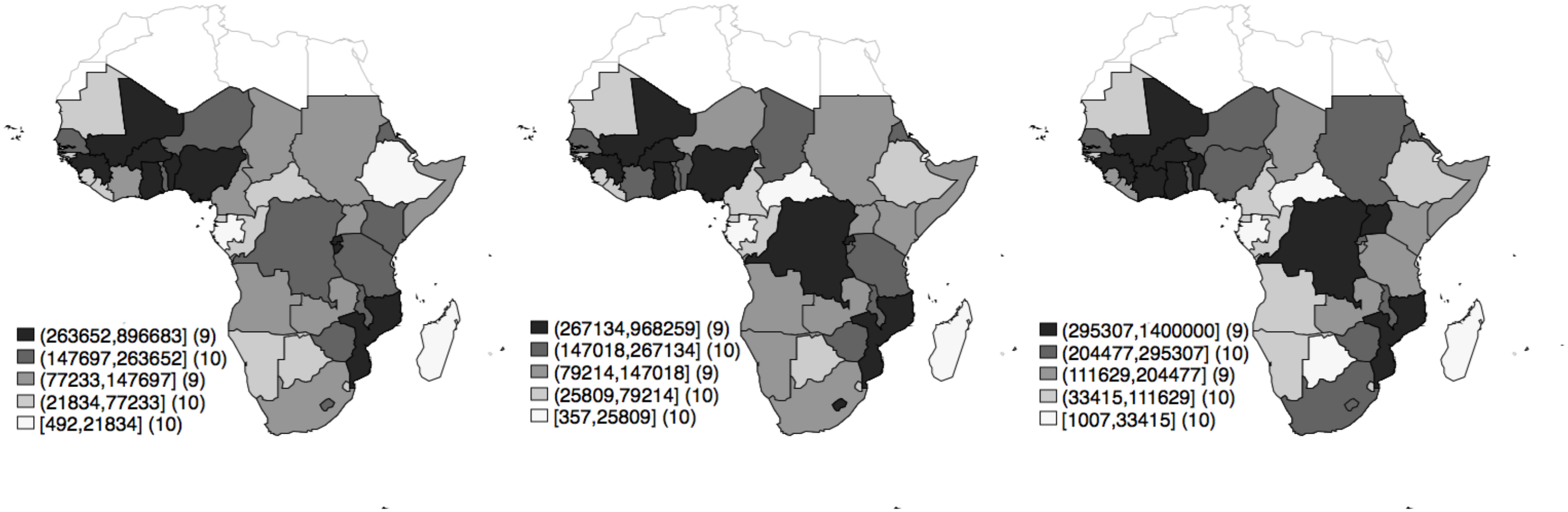
3.7.2 Figures

Figure 3.1: SSA migrant stocks by destination, 1980, 1990 and 2000



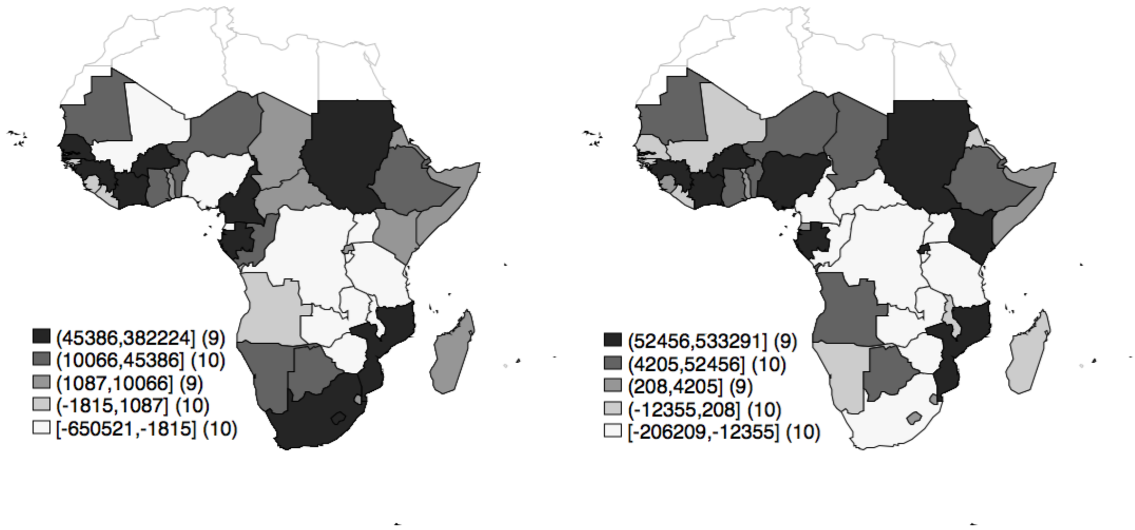
Source: Authors' calculations based on Global Bilateral Migration database, World Bank (2011)

Figure 3.2: SSA migrant stocks by origin, 1980, 1990 and 2000



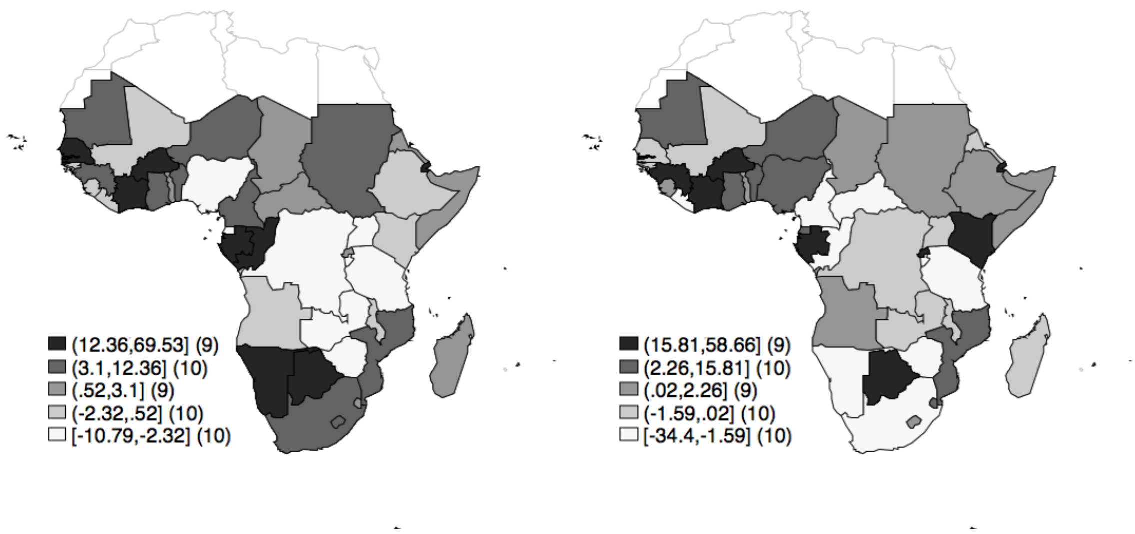
Source: Authors' calculations based on Global Bilateral Migration database, World Bank (2011)

Figure 3.3: SSA migrant stocks change by destination, 1980-1990 and 1990-2000



Source: Authors' calculations based on Global Bilateral Migration database, World Bank (2011)

Figure 3.4: SSA migrant stocks change by destination, 1980-1990 and 1990-2000 (population shares)



Source: Authors' calculations based on Global Bilateral Migration database, World Bank (2011)

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4

Determinants of the location choice of immigrants in Belgium 1990-2007[1]

[1]This chapter is the result of joint work with Prof. dr. Hubert Jayet, Prof. dr. Glenn Rayp and dr. Nadiya Ukrayinchuk.

Abstract

This chapter analyzes migratory streams to Belgian municipalities between 1990-2007. The Belgian population register constitutes a rich and unique database of yearly migrant inflows and stocks broken down by nationality, which allows us to empirically explain the location choice of immigrants at municipality level. Specifically, we aim at separating the network effect, captured by the number of previous arrivals, from other location-specific characteristics such as local labor or housing market conditions and the presence of public amenities. We expect labor and housing market variables to operate on different levels and develop a nested model of location choice in which an immigrant first chooses a broad area, roughly corresponding to a labor market, and subsequently chooses a municipality within this area. The spatial repartition of immigrants in Belgium seems determined by both network effects and local characteristics. The determinants of local attractiveness vary by nationality, as expected, but for all nationalities, they seem to dominate the impact of network effects.

JEL Classification: F22, O15, R23

Keywords: International migration, Location, Network effects, Nested logit

4.1 Introduction

The upsurge of migration flows in the last two decades has placed international migration high on the policy agenda of many countries. There is a thorough academic and political debate concerning potential explanations for this rise and adequate policies to manage it. Temporary migration schemes, the design of selective entry policies and the necessity of amnesties, are only some of the recent topics regarding migration that have been studied. An additional important issue relates to the spatial distribution of migrants once they arrive in the destination country. Their location pattern is conditioned by the distribution of natives (Le Bras and Labbé, 1993; Chiswick and Miller, 2004), but usually follows different dynamics that may exhibit a strong impact on the welfare of both natives and immigrants, on the spatial distribution of natives (Borjas, 1993, 2003; Friedberg and Hunt, 1995; Winkelman and Zimmerman, 1993) and also on the negative perception of immigrants to natives (Roux, 2004).

Both economic and sociological studies have analyzed the main characteristics of these patterns and their consequences. It is well established that immigrants of the same or similar ethnic origin tend to spatially concentrate much more than natives (see Carrington et al., 1996; Chau, 1997; Winters et al., 2001; Heitmueller, 2003; Bauer et al., 2002, 2005). This occurs because spatial nearness enables the formation of social networks, which tend to play a more important role for immigrants than for natives. By providing initial assistance to newcomers or help to face bureaucratic challenges in the destination country, social networks reduce some of the fixed initial costs that new immigrants come across. However, the presence of strong agglomerations of immigrants may have a negative effect on the assimilation and integration of both newcomers and second generations of immigrants.

Many surveys of international migration have shown that the existence of networks in the destination country has a positive effect on the propensity to migrate (Stark and Taylor, 1989; Massey and Denton, 1987; Bauer and Zimmermann, 1997; Tsuda, 1999). Only a limited number of studies, however, empirically estimated the effect of social networks on the location of immigrants within the host country. To our knowledge, this analysis has been conducted only for the United States (Bartel, 1989; Bauer et al., 2002), for Australia (Chiswick and Miller, 2004, 2005) and for France (Jayet and Ukrayinchuk, 2007). Despite the importance of many other European countries as destinations for immigrants, an analysis of their spatial repartition has not yet been explored, mainly because the required data is not available. The Belgian population register, however, constitutes a rich and unique database of yearly migrant inflows and stocks with a detailed breakdown by nationality and age cohort, which allows us to distinguish the immigrants of working age.

Besides providing insight into the spatial distribution of immigrants in Belgium through a descriptive analysis, this chapter contributes to the migration literature in two important ways. On the one hand, we develop a hierarchical (nested logit) model of the location choice of immigrants that is consistent with random utility maximization. Specifically, we expect labor and housing market variables to operate on a different level such that immigrants first select a region roughly corresponding to a labor market, and subsequently choose the municipality within this region which maximizes their utility. On the other hand, we investigate the relative importance of social networks versus these labor and housing market variables as well as other location specific characteristics such as the presence of public amenities, touristic attractiveness or distance to the nearest border.

The remainder of the chapter is structured as follows. Section 4.2 presents the main stylized facts concerning the location of immigrants in Belgium. Section 4.3 outlines the theoretical model of the location choice of immigrants and clarifies the choice for a nested structure. Section 4.4 elaborates the econometric methodology, specification tests and the empirical specification. Section 4.5 reports the empirical results from the nested model of location choice as well as from the decomposition of immigration probabilities, demonstrating to what extent the location pattern is determined by the genuine attractiveness of locations versus network effects, and from the analysis of the determinants of the local effects. Section 4.6 concludes.

4.2 The data

Before turning to the theoretical model, we briefly describe the current location pattern of immigrants in Belgium. The migration data were kindly provided by the Belgian Statistics Office. The Belgian population register constitutes a rich and unique database of migrant inflows and stocks broken down by nationality and age cohort, which allows us to distinguish the immigrants at working age (age 20 to 64). More specifically, it provides information on the number of immigrants arriving and living in each of the 588 municipalities between 1990 and 2007, covering 97 nationalities.

The population register keeps track of every foreigner who resides in Belgium for more than 3 months. Whereas legal immigrants are enrolled in the register of the municipality where they reside, illegal migrants do not appear in the immigration statistics as long as their situation has not been regularized.[2] Neither do asylum seekers, who are, as of 1995, enrolled in a special waiting register until they have been granted refugee status[3].

[2]Consequently, the database does not only record newcomers arriving from abroad but also migrants who already settled in a specific municipality and decide to move on to the next. It is thus not possible to distinguish internal migrants from international immigrants. Yet, we believe that our theoretical model applies to both types of migrants in the same manner: whether it concerns an internal or an international migrant, the choice for a certain location is expected to be made according to the same decision process.

[3]In fact, these refugees are not included in the immigrant streams as such but rather reported

Migration streams have been ever growing since the beginning of this period. Previous rises in immigration flows can be related to temporary favorable migratory conditions, following economic upsurges and labor shortages. The more recent migratory intensification is, on the other hand, not linked to proactive migration policies but rather to increased family reunification, European enlargement and rising asylum applications since 1990.

Table 4.1 presents migrant stocks by nationality for 2007[4] for the main nationalities[5], together with the share in total migrant stocks as well as their growth rates between 1990-2007. In 1990, the foreign population in Belgium amounted to 830 344, i.e. 8.36 percent of the total population. During the period 1990-2007, the migrant stock grew by nearly 4 percent, reaching 863 222 migrants in 2007 who account for 8.21 percent of the total population. The nationalities included in our sample add up to 67 percent of the total foreign population in 2007.

The most striking observation is that not the closest neighbors but rather Italians still form the largest foreign community in Belgium. Although their number systematically decreased since the 1990s, no less than one in five foreign residents still has the Italian nationality. Other important communities originate from France and the Netherlands. Their share in the total foreign population kept growing, and reached 14 and 13 percent in 2006, respectively. The largest non-European foreign communities are the Moroccan and Turkish communities with 80 613 and 39 665 residents, respectively. Their share in the total migrant stock,

in a different category 'adjustments'. This procedure obscures the real migratory movements, as illustrated by the reduced inflows recorded between 1995 and 1998. Yet, although information on the number of asylum applicants and refugees is available, details on these persons are fairly limited, which prohibits a simple merge of refugees and migrants to obtain a more accurate picture of current migratory streams.

[4]Given that the migrant stock is reported each year on January 1, it does not reflect changes in the migratory pattern which took place during the year of recording but rather captures the stock of migrants at the end of the preceding year.

[5]The selection of nationalities has been made based on the number of zeros in the migration statistics. Considering that we wish to find out whether the location choice differs depending on a person's nationality, we consider only a few nationalities, namely those with the least zeros.

Table 4.1: Migrant stocks: main nationalities, 2007

Origin	Units	Share (%)	Growth (%)
Total population	10511300		5.88
All foreigners	863222	100.00	3.96
Italy	175561	20.34	-27.17
France	120698	13.98	31.90
Netherlands	110513	12.80	82.52
Morocco	80613	9.34	-40.49
Turkey	39665	4.59	-50.08
Germany	37014	4.29	38.56
Poland	18032	2.09	282.52
Total sample	582096	67.43	-8.97

Notes: Authors' calculations based on data obtained from the Belgian Statistics Institute. *Share* denotes the share of total migrant stocks in Belgium, whereas *Growth* reflects the growth rate of migrant stocks between 1990 and 2007.

nevertheless, severely dropped since 1990 (by 40 and 50 percent respectively), following the 1991, 1995 and 2000 amendments to the naturalization law, which facilitated acquisition of the Belgian nationality[6]. An overview of yearly migrant stocks by nationality can be found in Table 4.10.

Focussing on immigrant flows, on the other hand, gives a very different picture. Table 4.2 illustrates absolute and relative numbers together with growth rates for immigrant flows in 2007 for both the whole immigrant population and the active subgroup (immigrants aged 20 to 64) as well as correlation coefficients between flows of active and retired immigrants. Immigrant flows from the nationalities in our sample represent 47 percent of the overall immigrant flow to Belgium in 2007. Yet, proportionally, these countries send out more active immigrants than other countries as their share in the overall immigrant flow to Belgium reaches 57 percent.

Neighboring countries France and the Netherlands have sent the most migrants to

[6]The largest impact on the number of naturalizations stems from the amendment of March 1, 2000, leading to 61 878 and 62 881 naturalizations in 2000 and 2001, respectively.

Table 4.2: Immigrant flows by type of activity: main nationalities, 2007

	Total (active and retired)			Active			Active vs. Retired
Origin	Units	Share (%)	Growth (%)	Units	Share (%)	Growth (%)	Correlation (%)
All foreigners	106576	100.00	70.09	78655	100.00	85.29	62.68
France	12269	11.51	104.11	9100	11.57	118.17	67.14
Netherlands	11370	10.67	91.96	7922	10.07	85.48	92.18
Poland	9393	8.81	1110.44	7930	10.08	1185.25	66.38
Morocco	7831	7.35	196.07	6065	7.71	213.11	68.21
Germany	3385	3.18	18.03	2532	3.22	20.06	41.08
Turkey	3180	2.98	30.01	2494	3.17	70.70	25.45
Italy	2708	2.54	2.46	2131	2.71	25.35	77.03
Total sample	50136	47.04	115.07	44668	56.79	85.29	

Notes: see Table 4.1. *Correlation* denotes the correlation coefficient between immigrants at working age and immigrants age 65 and older.

Belgium in 2007, i.e. around 22 percent of the total flow. Also Poland and Morocco turn out important source countries, together covering another 16 percent of total Belgian immigration in 2007. In addition, Polish migrant flows in 2007 are over 10 times their size in 1990, whereas 2007 inflows from Morocco have tripled compared to those in 1990. Immigrant flows from Turkey and Italy, on the other hand, also increased but at a slower pace. Whereas Italy is the most important origin country as far as concerns the total number of foreigners in Belgium, it represents only a small share, i.e. less than 3 percent, of Belgium's most recent migratory streams.

The correlation coefficients of active versus retired immigrant flows provides the motivation for not considering the immigrant population as a whole but rather focus on immigrants at working age in the empirical analysis. Correlation between these two types of immigrants is usually moderate, with specifically low values for German and Turkish immigrants. Only the Dutch inflow appears quite balanced across age groups. A summary of yearly migrant flows by nationality can be found in Tables 4.8 and 4.9 for all age groups and for active migrants, respectively.

The maps in Figure 4.1 illustrate the spatial distribution of immigrants across municipalities. Total migrant stocks as reported in 2007, on the left hand side, range from 11 to 54 416, whereas 2007 total immigrant flows start from zero and amount up to 10 001. Most foreigners are located in and around Brussels, along the French, Dutch and German border as well as in the Southern tip of Belgium neighboring Luxembourg and in the former mining districts in the Mid-West and North-East. Recent 2007 immigrant streams reveal more or less the same pattern, indicating a great deal of persistence in the migratory process.

The picture remains more or less the same if we consider immigrant rates instead, that is immigrant flows or stocks in shares of the population, as can be seen in Figure 4.2. However, it becomes clear that in the majority of municipalities in Flanders, immigrant rates are lower than those in Wallonia. In many municipalities in the North, less than 1.5 percent of the population is foreign, whereas in the South these percentages vary between 1.5 and 8. In many municipalities in and around Brussels, on the other hand, immigrant stocks account for 8 to 45 percent of the population with new inflows up to 6 percent of the local population in 2007.

Figure 4.3 displays immigrant flows by type of activity. A quick glance at the maps again illustrates the discrepancy between the location choice of active versus retired immigrants. Whereas both types of immigrants are highly concentrated in and around Brussels, immigrants at working age tend to be attracted to municipalities along the French border and in the very South, while retired immigrants prefer locations along the coastline, the Dutch border and to a lesser extent also the former mining district in the Sambre-Meuse Valley. This observation again demonstrates the need for a separate analysis for immigrants at working age versus the retired.

Also at the district level (see Figure 4.4), a certain degree of persistence in mi-

Figure 4.2: Total immigrant stocks and flows as a share of the population by municipality, 2007

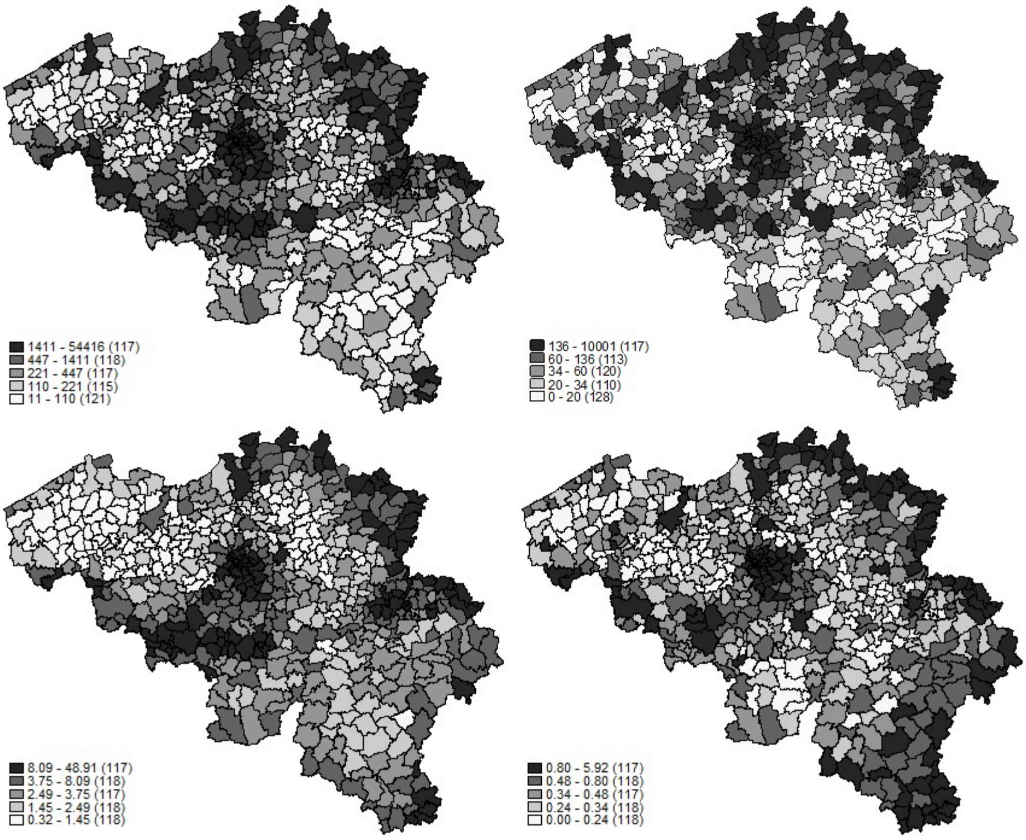
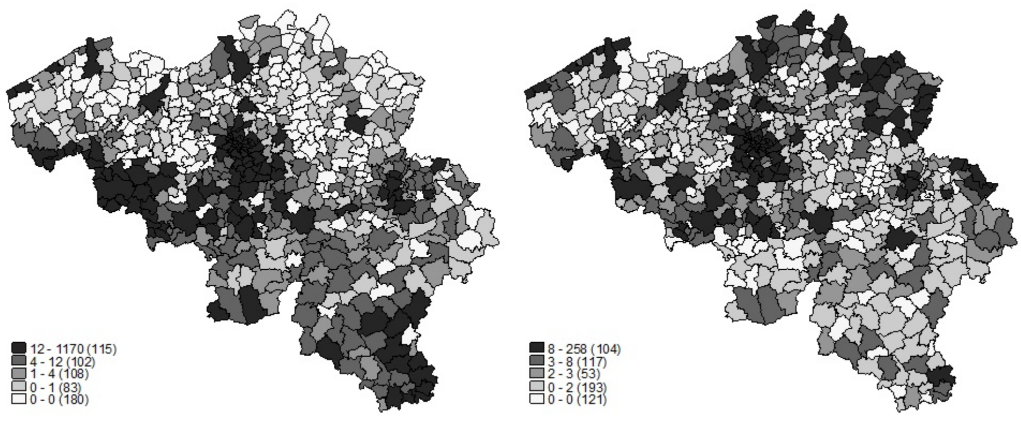


Figure 4.3: Active and retired immigrant flows as a share of the population by municipality, 2007

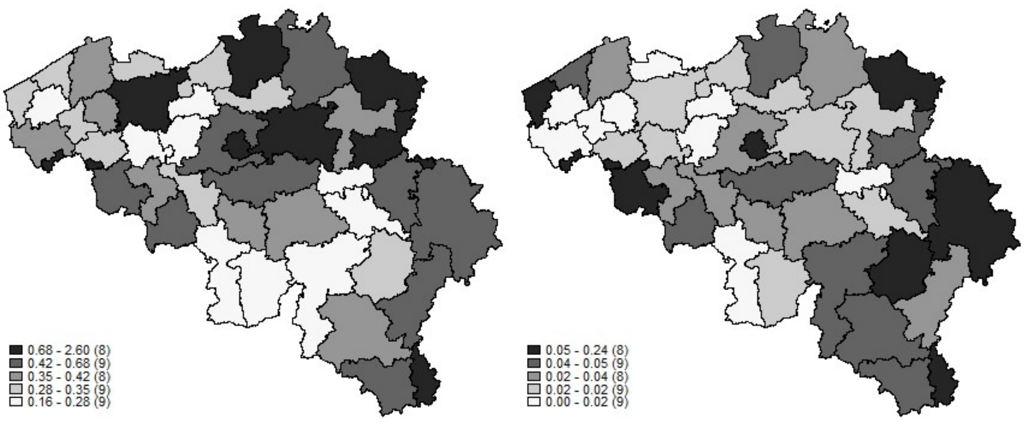


gratory movements can be observed. Foreigners are particularly concentrated in mid-Belgium around Brussels, Mons, Liege and Verviers, but also in the North-East with Antwerp as the main pole of attraction. Recent immigrant flows are no longer heading for Mons, Charleroi and Verviers but rather towards Ghent and Turnhout. Also in terms of population percentages, Brussels, the former mine districts and the North East host the most immigrants. Recent immigration flows however tend to be directed towards the Southern Brussels periphery, and less towards the former mine districts. Antwerp in the North and Arlon in the very South, on the other hand, appear as new settling destinations with immigrant rates varying between 1 and 3.4 percent of the population, respectively. Subdividing new immigrants according to their type of activity, as in Figure 4.6, again confirms the contrasting location choice of active versus retired immigrants. The pattern of retired immigrants differs from that of their active compatriots in the preference for Turnhout and Maaseik together with a reserve for the more recent destinations Ghent and Turnhout.

Finally, the spatial distribution of immigrants according to their country of origin can be found in Appendix Figures 4.8, 4.9 and 4.10. In general, Brussels is a major pole of attraction for all nationalities. Moreover, immigrants from neighboring countries tend to be located close to the border of their country of origin. Yet, the French can also be found in the municipalities close to Luxembourg, Germans favor also municipalities in Antwerp and, not surprisingly, Italians can be found especially in former mining districts. The Dutch are also located in Brussels, though to a lesser extent than the latter three nationalities, as well as in the Northern Ardennes. Finally, Moroccan, Turkish and Polish immigrants are spread more equally across the country, with slightly higher concentrations in mid Belgium and the former mining districts.

Figure 4.5: Total immigrant stocks and flows as a share of the population by district, 2007

Figure 4.6: Active and retired immigrant flows as a share of the population by district, 2007



4.3 A nested logit model of location choice

Consider a migrant who has decided to move to a certain destination country and who is supposed to choose a specific location i within this country. Our starting point is a standard choice model in which the migrant chooses the location that maximizes his or her utility at time t, net of moving costs, i.e. $U_{i,t}$. This utility may be measured using an indirect utility function: after choosing a location i, the migrant sells his or her labor and buys goods and services on local markets and simultaneously benefits from local externalities or publicly provided goods. As such, $U_{i,t}$ depends upon three types of location-specific characteristics: (i) expected labor market conditions and prices of goods, (ii) the presence of externalities such as amenities and public goods and (iii) migration costs. Information on local prices or wages is usually unavailable. As a proxy for these indicators, we might however use variables determining the equilibrium on the corresponding local markets. If information on local housing rent, for example, is unavailable, we can use information on the transactions of housing premises. The second type of location factors encompasses climatological conditions, the social environment, and the quality and quantity of infrastructure and public services in education and health. Finally, standard proxies for migration costs are distance to the country of origin as well as the presence of a border or a common language.

In addition to these location-specific factors, also social networks are expected to have an impact on the utility - and hence also the location choice - of an immigrant. As mentioned in the introduction, immigrants have a tendency to develop social and economic networks within their country of destination, which might help newcomers to find jobs and housing, to keep in touch with the culture of the origin country, and to alleviate liquidity constraints. From the migration literature, we know that these networks have both a strong local and national dimension: immigrants tend to be involved in social relations with migrants of the same country

of origin and typically locate close to each other. Because of their strong local dimension, currently existing national networks serve as a pull for newcomers: new immigrants are drawn to locations where previously arrived migrants of the same origin have developed local networks that can positively affect their utility.
Consider again the location factors of the first type, which in fact reflect labor and housing market conditions. These location factors are likely not to operate on the same level: it is expected that immigrants look for a job market in a fairly broad area - covering several municipalities - and subsequently look for housing within this area. This hypothesis implies a two stages process, which can be expressed uing a nested logit model of location choice.
More precisely, let us consider a set of I locations. Each location belongs to a higher-level area roughly corresponding to a labor market. Location i belongs to area $k = \kappa(i)$. The location choice involves a two-stage process: (i) choosing an area k and (ii) choosing a location i within area k. The utility of choosing location i is

$$U_{i,t} = (z_{i,t})' \beta + \left(z^*_{\kappa(i),t}\right)' \beta^* + \alpha_i + \zeta_{\kappa(i),t} + \varepsilon_{i,t} \tag{4.1}$$

where $z_{i,t}$ is a vector of location factors varying across locations and periods, while $z^*_{\kappa(i),t}$ varies across areas and periods, but takes the same value for all locations within the same area. The parameter α_i is a local effect measuring the impact of all the time invariant location factors while $\zeta_{\kappa(i),t}$ and $\varepsilon_{i,t}$ are random terms capturing the influence of all the unknown time varying location factors and personal characteristics. The local effect measuring the impact of all the time invariant location factors can be rewritten as

$$\alpha_i = (x_i)' \theta + \left(x^*_{\kappa(i)}\right)' \theta^* + \eta_i \tag{4.2}$$

where x_i a vector of location factors specific to location i and $x^*_{\kappa(i)}$ a vector of location factors common to all the locations included in the area $\kappa(i)$.

Both random terms, $\zeta_{\kappa(i),t}$ and $\varepsilon_{i,t}$, are iid, following Gumbel probability distributions. More precisely, for every k, the cdf of $\zeta_{k,t}$ is $F_1(\zeta) = \exp(-\exp(-\zeta/\mu_1))$ whereas, for every i, the cdf of $\varepsilon_{i,t}$ is $F_2(\varepsilon) = \exp(-\exp(-\varepsilon/\mu_2))$. Equivalently, both ζ/μ_1 and ε/μ_2 share the cdf $F(\xi) = \exp(-\exp(-\xi))$. Our utility function being defined up to a multiplicative constant, we can normalize without loss of generality, by choosing the identification restriction $\mu_1 + \mu_2 = 1$. The moment that the agent is choosing an area k, he knows the value of the random terms $\zeta_{1,t}, \ldots, \zeta_{K,t}$, but he does not know the value of the random terms $\varepsilon_{1,t}, \ldots, \varepsilon_{I,t}$. The value of the random terms $\varepsilon_{i,t}$ is revealed only once an area k has been chosen.

In the second stage, after the agent has chosen area k, he can only choose between alternative locations in area k. Within area k, $\left(z^*_{k,t}\right)' \beta^*$, $\zeta_{k,t}$ and $\left(x^*_k\right)' \theta^*$ do not differ across locations, so that the choice of a location maximises the reduced utility

$$U^2_{i,t} = (z_{i,t})' \beta + \alpha^2_i + \varepsilon_{i,t} = V_{i,t} + \varepsilon_{i,t} \tag{4.3}$$

where

$$V_{i,t} = (z_{i,t})' \beta + \alpha^2_i \tag{4.4}$$

$$\alpha^2_i = (x_i)' \theta + \eta_i \tag{4.5}$$

As such, the probability of the migrant choosing location i within area k, $p^2_{i,t}$, has a logit form,

$$p^2_{i,t} = \frac{\exp(V_{i,t}/\mu_2)}{\sum_{j,\kappa(j)=k} \exp\left(V_{j,t}/\mu_2\right)} = \exp\left(V_{i,t}/\mu_2 - \overline{V}_{k,t}/\mu_2\right) \tag{4.6}$$

where the inclusive value $\overline{V}_{k,t} = \mu_2 \ln\left(\sum_{j,\kappa(j)=k} \exp\left(V_{j,t}/\mu_2\right)\right)$ equals the expected indirect utility of the migrant at date t: $E\left[\max_{i,\kappa(i)=k} U^2_{i,t}\right] = \overline{V}_{k,t}$.

In the first stage, as the migrant does not know the final location he will choose in the second stage, he only chooses the area maximizing the expected utility,

$$E\left[U_{i,t}|\kappa(i)=k\right] = \left(z^*_{k,t}\right)'\beta^* + (x^*_k)'\theta^* + E\left[\max_{i,\kappa(i)=k} U^2_{i,t}\right] + \zeta_{k,t}$$
$$= \left(z^*_{k,t}\right)'\beta^* + (x^*_\kappa)'\theta^* + \overline{V}_{k,t} + \zeta_{k,t}. \tag{4.7}$$

Consequently, the probability of the migrant choosing area k, $p_{k,t}$, has a logit form,

$$p^1_{k,t} = \frac{\exp\left(\frac{\left(z^*_{k,t}\right)'\beta^* + \left(x^*_k\right)'\theta^* + \overline{V}_{k,t}}{\mu_1}\right)}{\sum_n \exp\left(\frac{\left(z^*_{n,t}\right)'\beta^* + (x^*_n)'\theta^* + \overline{V}_{n,t}}{\mu_1}\right)}. \tag{4.8}$$

It should be mentioned that, even though there are a number of similarities, our model is not completely identical to the nested logit model developed by McFadden (1978). Both models satisfy the independence of irrelevant alternatives (IIA) property when the choice is restricted to alternative locations situated within the same area. The property however no longer holds when alternatives are located in different areas. There is yet an important difference: in McFadden's nested logit model, the agent always chooses the best alternative, i.e. the location from the set I that offers the highest utility. McFadden (1978) defines $p^1_{k,t}$ as the probability that the best alternative is a location within area k, while $p^2_{i,t}$ is the probability that the best alternative is location i, knowing that it is situated in area $\kappa(i)$. The choice process in McFadden (1978) thus assumes that immigrants are fully informed. In our model, on the other hand, it is assumed that immigrants do not have full information and as such cannot make completely rational decisions. It is an actual two-stage decision model with uncertainty in which the agent chooses, in the first stage, the area maximizing his expected utility and, in the second stage, the best alternative within this area. There is no guarantee, however, that this is also the location with the highest utility among all locations in the set I. Contrary to McFadden's model, the agent is thus not necessarily choosing the best location: if the best alternative is situated in an area where the other locations are bad enough for the expected utility to be low, the agent does not choose this area in the first stage and subsequently cannot choose the best alternative in the second stage. We believe that this more realistically reflects an immigrant's decision making process.

Our second point is that, if $\mu_1 = \mu_2$, then $U_{i,t}$ only has one random term, $\varepsilon_{i,t}$, which is uncorrelated across alternatives. In this case, our model boils down to a standard logit model satisfying the IIA property. We can thus test for the validity of the IIA assumption by testing the null hypothesis $\mu_1 = \mu_2$.

4.4 Empirical analysis

4.4.1 Estimation method

Although the estimation follows standard methods for nested logit models, our empirical analysis stumbles across some additional complications. We first maximize the reduced utility from equation (4.3), i.e. the second stage in our nested logit model. There are three points to note, however. First, given that alternatives to the choice of location i are other municipalities included in area $\kappa(i)$, the set of available alternatives depends upon the area. Second, given that the choice problem is invariant with respect to the scale factor μ_2, we can only estimate the scaled coefficients, β/μ_2 and α_i^2/μ_2. Third, because the choice problem within an area is invariant with respect to an additive constant, the local factors α_i^2 are not identified and we can only estimate the scaled difference $\left(\alpha_i^2 - \alpha_{r(\kappa(i))}^2\right)/\mu_2$ where, for every area k, $r(k)$ is an arbitrarily chosen reference location. Specifically, in the second stage, we maximize the following log likelihood:

$$LL = \sum_{i,t} n_{i,t} \ln p_{i,t}^2 \tag{4.9}$$

where

$$p_{i,t}^2 = \frac{\exp\left((z_{i,t})' b + a_i^2\right)}{\sum_{j,\kappa(j)=k} \exp\left(\left(z_{j,t}\right)' b + a_j^2\right)} \tag{4.10}$$

with $b = \beta/\mu_2$ and $a_i^2 = \left(\alpha_i^2 - \alpha_{r(\kappa(i))}^2\right)/\mu_2$. The maximum likelihood estimates $\hat{b}$ of b and $\hat{a}_i^2$ of a_i^2 can then be used to calculate the estimated inclusive value for every area k and year t as

$$\hat{V}_{k,t} = \ln\left(\sum_{j,\kappa(j)=k} \exp\left((z_{i,t})' \hat{b} + \hat{a}_i^2\right)\right). \tag{4.11}$$

Note that $\hat{V}_{k,t}$ is not an estimator of the true unknown inclusive value,

$$\begin{aligned} \overline{V}_{k,t} &= \mu_2 \ln\left(\sum_{j,\kappa(j)=k} \exp\left(\frac{V_{j,t}}{\mu_2}\right)\right) = \mu_2 \ln\left(\sum_{j,\kappa(j)=k} \exp\left((z_{i,t})' b + a_i^2 + \frac{\alpha_{r(k)}^2}{\mu_2}\right)\right) \\ &= \mu_2 \ln\left(\sum_{j,\kappa(j)=k} \exp\left((z_{i,t})' b + a_i^2\right)\right) + \alpha_{r(k)}^2. \end{aligned} \tag{4.12}$$

$\overline{V}_{k,t}$ may thus be estimated as $\mu_2 \hat{V}_{k,t} + \alpha_{r(k)}^2$ with μ_2 and $\alpha_{r(k)}^2$, however, still unknown.

Subsequently, we proceed to the estimation of the first stage. Replacing $\overline{V}_{k,t}$ in (4.7) by its estimated value, we get

$$E\left[U_{i,t}|\kappa(i) = k\right] = \left(z_{k,t}^*\right)' \beta^* + \left(x_k^*\right)' \theta^* + \mu_2 \hat{V}_{k,t} + \alpha_{r(k)}^2 + \zeta_{k,t}. \tag{4.13}$$

Again, three points are worth noting. First, because θ^* and the vector of local effects $\left(\alpha_{r(1)}^2, \ldots, \alpha_{r(K)}^2\right)$ are not identified independently of each other, we can only estimate the "area effects" $\alpha_k^1 = \left(x_k^*\right)' \theta^* + \alpha_{r(k)}^2$. Second, when no identification condition is specified, only the scaled coefficients, $b^* = \beta^*/\mu_1$, $\lambda = \mu_2/\mu_1$ and α_k^1/μ_1 are identified[7].Third, the "area effects" themselves are not fully identified. Only the scaled differences to a reference area (say area K), $a_k^1 = \left(\alpha_k^1 - \alpha_K^1\right)/\mu_1$

[7]Note that, contrary to McFadden's nested logit model, λ is not restricted to the unit interval for the model to be consistent with utility maximization, it only needs to be non-negative.

can be estimated. Specifically, in the first stage of the nested logit model, we maximize the following log likelihood:

$$LL = \sum_{k,t} N_{k,t} \ln p^1_{k,t} \tag{4.14}$$

where

$$N_{k,t} = \sum_{i,\kappa(i)=k} n_{i,t} \tag{4.15}$$

$$p^1_{k,t} = \frac{\exp\left(\left(z^*_{k,t}\right)' b^* + a^1_k + \lambda \hat{V}_{k,t}\right)}{\sum_m \exp\left(\left(z^*_{m,t}\right)' b^* + a^1_m + \lambda \hat{V}_{m,t}\right)} \tag{4.16}$$

which gives maximum likelihood estimates $\hat{\lambda}$ of λ, $\hat{b}^*$ of b^* and $\hat{a}^1_k$ of a^1_k. Subsequently using the equalities $\lambda = \mu_2/\mu_1$ and $\mu_1 + \mu_2 = 1$, we get estimates for μ_1 and μ_2:

$$\hat{\mu_1} = \frac{1}{\hat{\lambda}+1} \tag{4.17}$$

$$\hat{\mu_2} = \frac{\hat{\lambda}}{\hat{\lambda}+1}. \tag{4.18}$$

Then, combining

$$\alpha_i = (x_i)' \theta + \left(x^*_{\kappa(i)}\right)' \theta^* + \eta_i \tag{4.19}$$

$$\alpha^2_i = (x_i)' \theta + \eta_i \tag{4.20}$$

$$\alpha^1_k = (x^*_k)' \theta^* + \alpha^2_{r(k)} \tag{4.21}$$

gives

$$\alpha_i = \alpha^1_{\kappa(i)} + \alpha^2_i - \alpha^2_{r(\kappa(i))} \tag{4.22}$$

$$\alpha_{r(K)} = \alpha^1_K + \alpha^2_{r(K)} - \alpha^2_{r(K)} = \alpha^1_K \tag{4.23}$$

for any location i and reference location $i = r(K)$ within the reference area K, respectively. Now, using the fact that

$$\mu_2 a_i^2 = \alpha_i^2 - \alpha_{r(\kappa(i))}^2 \tag{4.24}$$

$$\mu_1 a_k^1 = \alpha_k^1 - \alpha_K^1 \tag{4.25}$$

we get

$$a_i \equiv \alpha_i - \alpha_{r(K)} = \alpha_i - \alpha_K^1 \tag{4.26}$$

$$= \left(\alpha_{\kappa(i)}^1 - \alpha_K^1\right) + \left(\alpha_i^2 - \alpha_{r(\kappa(i))}^2\right) \tag{4.27}$$

$$= \mu_1 a_{\kappa(i)}^1 + \mu_2 a_i^2 \tag{4.28}$$

which may be estimated as

$$\hat{a}_i = \hat{\mu}_1 \hat{a}_{\kappa(i)}^1 + \hat{\mu}_2 \hat{a}_i^2 = \frac{\hat{a}_{\kappa(i)}^1 + \hat{\lambda}\hat{a}_i^2}{\hat{\lambda}+1}. \tag{4.29}$$

These estimated local effects can then be used to estimate θ and θ^* in

$$a_i = \alpha_i - \alpha_{r(K)} = \left(x_i - x_{r(K)}\right)'\theta + \left(x_{\kappa(i)}^* - x_K^*\right)'\theta^* + \eta_i - \eta_{r(K)} \tag{4.30}$$

which, using the estimated values for a_i, transforms to

$$\hat{a}_i = \left(x_i - x_{r(K)}\right)'\theta + \left(x_{\kappa(i)}^* - x_K^*\right)'\theta^* + \eta_i - \eta_{r(K)} + u_i \tag{4.31}$$

with u_i a random error term.

This equation may be estimated using standard least squares (OLS) methods. One must however account for potential autocorrelation generated by the nested and spatial structure of locations that are situated in the same area or spatially correlated, respectively. Both spatial lag models (SAR) and spatial error models (SEM) have been used to capture this geographic interdependence Anselin (1988). In fact, the spatial econometrics literature provides both theoretic and econometric motivations for the use of spatial regression models. An example of the former concerns migration regulations, which are difficult to measure in practice because of their qualitative nature and, therefore, often omitted in empirical specifications. They form, however, an important barrier to migration and are likely to be correlated across countries. Governments might, for instance, decide to set in place certain policy measures after having observed those set by neighboring countries. This type of spatial interdependence might be explicitly integrated in the formal specification of the theoretical model. Yet, it might also be motivated from an econometric perspective by looking upon bilateral flows as describing a diffusion process over space with a time lag. This form of spatial dependence typically shows up in cross-sectional models with a spatial lag of the dependent variable. Another important econometric motivation for the use of spatial regressions concerns the presence of omitted latent influences that are spatial in nature, typically leading to a spatial Durbin model (SDM) with spatial lags of both the dependent and explanatory variables (LeSage and Pace, 2009). Again, migration policy appears an obvious candidate given that it is often an omitted latent influence that is both correlated with the explanatory variables and across locations.

We do not a priori assume spatial dependence but rather use ordinary and robust Lagrange Multiplier (LM) tests to evaluate its presence (in the form of a spatial lag or spatial error) in the local effects. Subsequently, we follow the approach of LeSage and Pace (2008), LeSage and Pace (2009) and Elhorst (2010), which starts from a spatial Durbin model, the most general model of spatial dependence, and relies on specification tests to determine whether this model can be simplified to a SAR or SEM model. LeSage and Pace (2009) show that the SDM is less affected by omitted variable bias than a model that ignores spatial dependence. This holds when the omitted variable is truly involved in the data generating process, but also when it is not, its inclusion does not lead to bias in the estimates. Consequently, the authors suggest relying on a model that includes spatial lags of the dependent and explanatory variables even if this seems counterintuitive at first sight.

It should be noted that our estimation method is robust to zero flows. More precisely, even though the period is long (our sample has 18 years), there are locations that never received any immigrant during the whole period. For these locations, the flow is zero every year, which implies that the estimated probability of receiving a migrant is zero and that the estimator of the local fixed effect, $\hat{\alpha}_i$, is minus infinity. Consequently, these observations are dropped from our sample. Yet, this does not bias our results because of the following reason. In the first stage, the IIA property holds within every area, so that restricting the choice set within an area still results in consistent estimates. Analogously, in the second stage, the IIA property holds for the choice across areas, so that again restricting the choice set still leads to consistent estimates.

The estimation approach outlined above allows us to carry out several specification tests. A first series of tests looks at the value $\hat{\lambda}$, the coefficient of the inclusive value. First, if $\hat{\lambda} = 1$ (or, equivalently, $\hat{\mu}_1 = \hat{\mu}_2$), the probabilities predicted by our model are exactly the same as the probabilities predicted by the standard logit model. As such, a test that our model reduces to the standard logit model (and that the IIA assumption holds) is a test of the null hypothesis $\hat{\lambda} = 1$. Second, in order to ensure that our model is compatible with random utility maximization, $\hat{\lambda}$ should be non-negative. When it moreover falls in the interval [0,1], our model is equivalent to the nested logit model developed by McFadden (1978). Finally, when $\hat{\mu}_1 = 0$, there is no uncertainty in the first stage, i.e. the choice of an area, so that all immigrants concentrate in the same area. However, within this area, they may still spread across different locations. Third, when $\hat{\mu}_2 = 0$, there is no uncertainty in the second stage, i.e. the choice of a location within an area: within each area, all the immigrants concentrate in the same location. However, at the area level, they may spread across different areas.

4.4.2 Empirical specification

In order to empirically investigate the relative importance of network effects and location characteristics, we need to identify arguments for $z_{i,t}$ and $z^*_{k,t}$. The vector of location-specific factors, $z_{i,t}$, includes a measure of the size of the local network. Following standard practice, the latter is approximated by the local stock of migrants from the same origin country at the end of the previous period, $s_{i,t-1}$. Yet, we believe that not only the network effect of the location itself but also that of neighboring locations might act as a pull towards newcomers. As argued above, the choice for a specific location might be linked to the spatial nearness of the social network, but this does not necessarily require the network is situated in the exact same location. Therefore, our empirical specification includes also the average migrant stock in the direct neighbors to each location (whether or not they belong to the same area), denoted $sn_{i,t-1}$.

In order to capture housing market conditions, we include average prices and the number of transactions for both houses (i.e. $hp_{i,t}$ and $ht_{i,t}$) and apartments (i.e. $ap_{i,t}$ and $at_{i,t}$) at the local level. We have no a priori expectations about the sign of average housing prices: a negative sign suggests immigrants prefer locations where housing is relatively cheap, whereas a positive sign might signal that immigrants from a certain country prefer locations with a higher social standard. In order to eliminate the rising trend in housing prices during the sample period, we take averages with respect to the cross-sectional mean. For the number of housing transactions we expect a positive sign in line with the idea that a more active housing market facilitates the acquisition of accommodation in the destination. As argued above, labor market conditions are expected to play at the area level rather than the local level. As such, we use the unemployment rate, $u_{k,t}$, at the area level as a proxy for area-specific job opportunities, $z^*_{k,t}$.[8] Hence, assuming a logarithmic utility function, we define

$$(z_{i,t})'\beta = \beta_1(\ln s_{i,t-1}+1)+\beta_2(\ln sn_{i,t-1}+1)$$
$$+\beta_3 \ln hp_{i,t}+\beta_4 \ln ap_{i,t}+\beta_5 \ln ht_{i,t}+\beta_6 \ln at_{i,t} \quad (4.32)$$
$$(z^*_{k,t})'\beta^* = \beta^*_1 u_{i,t-1} \quad (4.33)$$

where we add unity to the migrant stock first in order to avoid taking the log of zero.

Furthermore, recall that α_i is considered to capture all the time invariant location factors, such as overall capacity, migration costs or the presence of public amenities. It is straightforward to see that larger locations are able to host more immigrants. Popular proxies for the size of locations and as such also their hosting capacity are surface (sf_i) and population density (pd_i). In order to control for these size effects, we include both measures in our empirical specification. Migration costs are often proxied by the distance to the origin country or the presence of a common border. Both indicators have proven to influence monetary expenses as well as non-monetary opportunity costs (such as foregone earnings while traveling and finding a job) incurred by the migrant (see e.g. Karemera et al., 2000; Gallardo-Sejas et al., 2006; Lewer and Van den Berg, 2008; Pedersen et al., 2008; Mayda, 2010). Given the relatively small size of the locations in our sample, there is not much variation in the distance between origin country and destination location and, as such, its inclusion in the empirical specification does not make much sense.[9] The spatial concentration of immigrants from neighboring countries along

[8]Ideally, we would also include a measure of average wages to capture expected income opportunities. Unfortunately, data on average wages is unavailable. One solution would be to proxy for it using average income declarations per inhabitant. The latter is however severely correlated with housing prices which indicates that it captures also other effects besides average income opportunities. Consequently, we do not include this measure in our empirical specification.

[9]The same holds for variables capturing environmental conditions: given the small size of

the border of their country of origin, however, suggests that the presence of a common border positively influences migration to those locations. Yet, this positive effect is not confined to the strict set of locations actually situated along the border (see Figures 4.1 and 4.2), but rather seems decaying in nature. To capture this, we incorporate the minimal distance to the nearest border, dbo_i on top of the minimal distance to Brussels, dbr_i, which is supposed to capture the relative attractiveness of the capital region as the principal transportation hub with the largest international airport and train connections to international destinations and other locations within Belgium.

Besides geographical proximity, also externalities such as the presence of amenities and public goods are expected to foster the genuine attractiveness of locations. To proxy for these externalities, we include the number of hospitals, ho_i, secondary schools, sc_i, and sport clubs, sp_i, as a share of the local population. Furthermore, we account also for the size of the motorway network as a share of the total surface, mw_i, and for the touristic attractiveness of municipalities, i.e. hotel occupancy or the number of nights per inhabitant, to_i. Also the rate of urbanization might have an influence on the location choice. In order to control for this effect, we introduce a measure of the morphological rate of urbanization (for which correlation with population density is fairly limited).

Finally, we expect that also cultural proximity, captured by the presence of a common language, cl, facilitates adaptation and integration in the new environment which in turn reduces the costs of migration and increases migration to those locations (see also Karemera et al., 2000; Gallardo-Sejas et al., 2006; Lewer and Van den Berg, 2008; Pedersen et al., 2008). As such, the local effect, α_i, can be

Belgian municipalities and Belgium as a whole, there is not much climatological variation across locations which renders its inclusion uninformative.

written as

$$
\begin{aligned}
\alpha_i = {} & \gamma_0 + \gamma_1 \ln sf_i + \gamma_2 \ln pd_i + \gamma_3 \ln dbo_i + \gamma_4 \ln dbr_i \\
& + \gamma_5 \ln ho_i + \gamma_6 \ln sc_i + \gamma_7 \ln sp_i \\
& + \gamma_8 \ln mw_i + \gamma_9 \ln to_i + \gamma_{10} \ln ur_i + \gamma_{11} cl_i
\end{aligned} \tag{4.34}
$$

Consequently, combining equations (4.32), (4.33) and (4.34) we can rewrite equation (4.1) as

$$
\begin{aligned}
U_{i,t} = {} & \gamma_0 + \beta_1 (\ln s_{i,t-1} + 1) + \beta_2 (\ln sn_{i,t-1} + 1) \\
& + \beta_3 \ln hp_{i,t} + \beta_4 \ln ap_{i,t} + \beta_5 \ln ht_{i,t} + \beta_6 \ln at_{i,t} + \beta_1^* u_{i,t-1} \\
& + \gamma_1 \ln sf_i + \gamma_2 \ln pd_i + \gamma_3 \ln dbo_i + \gamma_4 \ln dbr_i \\
& + \gamma_5 \ln ho_i + \gamma_6 \ln sc_i + \gamma_7 \ln sp_i \\
& + \gamma_8 \ln mw_i + \gamma_9 \ln to_i + \gamma_{10} \ln ur_i + \gamma_{11} cl_i + \zeta_{\kappa(i),t} + \varepsilon_{i,t}
\end{aligned} \tag{4.35}
$$

which is our basic empirical model of location choice that will be estimated in the next section. Note that equation (4.35) encompasses two sources of persistence: at date t, location i might be attractive because of (i) the effect of the time invariant location factors, measured by α_i, or (ii) because it has attracted immigrants in the past, who developed a local network, the size of which is measured by $s_{i,t-1}$.
Most of the data for the explanatory variables has been collected from the Belgian Statistics Office. This is the case for migration statistics but also for housing, labor market and geographical variables as well as information on the motorway network, hotel occupancy, urbanization and the local official language. For apartment prices, part of the data is missing. To deal with this, we plug in zeros for all missing observations and include a dummy variable coded one if data in the original value was missing and zero otherwise. This procedure however does not affect our estimation results (the results for the remaining variables are not affected by

the inclusion of apartment prices in the empirical specification). Other sources include the Belgian Hospitals Association for the number of hospitals, the Federation Wallonia-Brussels for data on the number of secondary schools and sport clubs in the French speaking community and DG Belgium for the same data in the German speaking community. For the Flemish speaking region, these data have been obtained from the Flemish Ministry of Education and Training and Bloso, the sport administration of the Flemish government, respectively. Whereas the data on the number of secondary schools are reasonably compatible, this is not true for the number of sport clubs. In order to guarantee consistency, we subtract the regional mean from the number of sport clubs for each municipality.

4.5 Estimation results

The estimations are carried out for the whole population of immigrants and for the seven most important national origins: France, Germany, Italy, Morocco, The Netherlands, Poland and Turkey. The locations are the 588 Belgian municipalities. Areas (i.e. groups of municipalities) are defined as the 43 Belgian districts. Given that labor market variables are a crucial element in our theoretical model of the location decision, the analysis is performed only for immigrants at working age.[10] In what follows, we first compare the results from the hierarchical nested logit model to those from the non-nested logit model. The latter serves as a benchmark, which allows us to test for the relevance of the nested structure and to analyze its impact on the estimated network effects. Subsequently, we perform a decomposition of the immigration rate to evaluate the relative importance of the two sources of persistence: network effects and location factors. Finally, we regress the estimated local effects on the time invariant location characteristics in

[10]Because for some variables in our model there are no data before 1994, our estimations cover the period 1994-2007.

order to investigate their role in the location decision.

4.5.1 Multinomial logit and nested logit model estimates

Before examining the estimation results from the nested logit model, we first look at the standard (non nested) multinomial logit estimates, displayed in Table 4.3. The estimated network effect is positive and highly significant for all nationalities except for Germans. Specifically, it varies between 0.061 and 0.302 for German and Turkish immigrants, respectively. Average stocks in neighboring municipalities also act as a pull for migrants of all nationalities except for the Dutch. The effect is generally of the same size as the direct effect, reaching a value of 0.259 for Germans and even 0.798 for Italians. Against expectations, the negative effect for Dutch immigrants seems to overcompensate the positive effect of migrant stocks in the location itself. For the immigrant population as a whole, on the other hand, both coefficients are negatively significant. This is not surprising given that the overall immigrant flow and stock group a multitude of nationalities, rendering the notion of a national network inapplicable. Only when network effects could be interpreted as some kind of herd effects (as is often the case in a context of imperfect information), we would expect a positive coefficient (see e.g. Bauer et al., 2007; Epstein, 2008).

As far as concerns the housing market variables, we find a positive (mostly significant) impact of house prices for immigrants from neighboring countries as well as Turks. The coefficient appears negatively significant for Moroccans and Poles. The sign of apartment prices is less ambiguous: we find a negative impact for all nationalities except for Italians (though insignificant). With respect to the number of transactions, we find a positive significant impact for Germans, Dutch, Poles and the immigrant population as a whole, in line with our expectations. The same is found for housing prices, though only for Moroccans and the Dutch. For Ger-

Table 4.3: First step estimates, multinomial logit model

Dependent variable: n_{it} Sample period: 1994-2007

Variable	DE	FR	IT	MA	NL	PL	TR	TOT
$\ln s_{i,t-1}$	0.061	0.276***	0.173**	0.169***	0.277***	0.147***	0.302***	−0.165***
	(0.166)	(0.000)	(0.012)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\ln sn_{i,t-1}$	0.259***	0.347***	0.798***	0.073**	−0.422***	0.181***	0.119***	−0.050***
	(0.001)	(0.000)	(0.000)	(0.048)	(0.000)	(0.000)	(0.000)	(0.006)
$\ln ph_{i,t}$	0.736***	0.027	0.217**	−0.543***	0.792***	−0.633***	0.292***	0.219***
	(0.000)	(0.570)	(0.014)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\ln pa_{i,t}$	−0.136***	−0.044**	0.052	−0.059*	−0.005	−0.153***	−0.195***	−0.039***
	(0.000)	(0.010)	(0.182)	(0.068)	(0.776)	(0.000)	(0.000)	(0.000)
$\ln th_{i,t}$	−0.112***	0.014	−0.084**	0.125***	0.097***	−0.213***	−0.130***	−0.003
	(0.000)	(0.438)	(0.021)	(0.000)	(0.000)	(0.000)	(0.001)	(0.614)
$\ln ta_{i,t}$	0.061***	0.017	−0.023	0.027	0.048***	0.143***	0.017	0.036***
	(0.003)	(0.218)	(0.381)	(0.208)	(0.000)	(0.000)	(0.495)	(0.000)
$\ln u_{i,t}$	0.033**	−0.108***	0.084	0.073	−0.075**	−0.030	−0.198***	−0.057***
	(0.476)	(0.005)	(0.220)	(0.149)	(0.015)	(0.655)	(0.001)	(0.000)
$\ln dph_{i,t}$	−15.430		−2.479	−0.551	0.023	−2.269	−1.994	−0.461**
	(0.997)		(0.830)	(0.929)	(0.903)	(0.819)	(0.737)	(0.014)
$\ln dpa_{i,t}$	−0.398***	−0.220***	0.222	−0.329**	0.071	−0.514***	−0.914***	−0.132***
	(0.000)	(0.002)	(0.191)	(0.017)	(0.363)	(0.002)	(0.000)	(0.000)
LL	-141366	-385608	-115998	-252958	-379672	-141260	-112296	-3679691

Note: *P*-values in parenthesis. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively.

mans, Italians, Poles and Turks, we find a negative influence of the number of house transactions. Finally, as expected, we find a negative significant impact of unemployment for French, Dutch and Turkish immigrants, but a positive significant effect for Germans.

Table 4.4 presents the estimation results of the nested logit model described above. The model systematically converges and the results are robust to changes in the initial value of the coefficients in the maximization algorithm.

First of all, for both definitions of an area, we find a positive significant coefficient for the inclusive value (i.e. λ) for all nationalities in our analysis. Consequently, the estimation results are conform with random utility maximization. In general, the coefficients for the inclusive value does not fall within the $[0,1]$ interval as expected from McFadden's (1978) nested logit model.

Table 4.4: First step estimates, nested logit model

Dependent variable: n_{it} Sample period: 1994-2007

Variable	DE	FR	IT	MA	NL	PL	TR	TOT
$\hat{V}_{k,t}$	1.260^{***}	0.357^{***}	1.966^{***}	0.831^{***}	1.250^{***}	1.238^{***}	0.990^{***}	0.286^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\ln s_{i,t-1}$	0.059	0.246^{***}	0.022	0.195^{***}	0.134^{***}	0.071^{***}	0.296^{***}	-0.086^{***}
	(0.244)	(0.000)	(0.786)	(0.000)	(0.002)	(0.002)	(0.000)	(0.000)
$\ln sn_{i,t-1}$	0.446^{***}	0.060	0.465^{**}	0.169^{***}	-0.452^{***}	0.047	0.138^{**}	-0.340^{***}
	(0.000)	(0.562)	(0.016)	(0.009)	(0.000)	(0.334)	(0.010)	(0.000)
$\ln ph_{i,t}$	0.038	0.383^{***}	0.010	-0.351^{***}	0.458^{***}	-0.764^{***}	0.032	0.077^{***}
	(0.691)	(0.000)	(0.947)	(0.000)	(0.000)	(0.000)	(0.835)	(0.001)
$\ln pa_{i,t}$	-0.066^{**}	-0.005	0.001	-0.022	0.001	-0.070	-0.145^{***}	0.010
	(0.012)	(0.783)	(0.979)	(0.555)	(0.959)	(0.105)	(0.002)	(0.137)
$\ln th_{i,t}$	0.071^{*}	-0.014	-0.061	0.170^{***}	0.152^{***}	-0.102^{**}	0.012	0.040^{***}
	(0.066)	(0.594)	(0.245)	(0.000)	(0.000)	(0.011)	(0.837)	(0.000)
$\ln ta_{i,t}$	0.031	0.007	-0.066^{**}	0.037	0.044^{***}	-0.006	0.022	0.006
	(0.187)	(0.661)	(0.033)	(0.125)	(0.000)	(0.831)	(0.461)	(0.269)
$\ln u_{i,t}$	-0.337^{***}	0.060	0.132^{*}	-0.018	-0.258^{***}	0.022	-0.285^{***}	-0.016
	(0.000)	(0.242)	(0.066)	(0.737)	(0.000)	(0.777)	(0.000)	(0.240)
$\ln dph_{i,t}$	-2.317		-2.816	-0.726	-0.039	-7.034	-2.091	-0.323^{*}
	(0.775)		(0.789)	(0.912)	(0.842)	(0.954)	(0.782)	(0.087)
$\ln dpa_{i,t}$	-0.236^{**}	-0.037	-0.044	-0.170	0.083	-0.374^{**}	-0.730^{***}	0.021
	(0.040)	(0.650)	(0.818)	(0.276)	(0.332)	(0.040)	(0.000)	(0.495)
$\hat{\mu}_1$	0.442^{***}	0.737^{***}	0.337^{***}	0.546^{***}	0.444^{***}	0.447^{***}	0.502^{***}	0.777^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\hat{\mu}_2$	0.558^{***}	0.263^{***}	0.663^{***}	0.454^{***}	0.556^{***}	0.553^{***}	0.498^{***}	0.223^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LL_1	-66339	-175393	-50252	-117620	-174903	-66439	-40006	-1600308
LL_2	-75111	-210246	-65754	-135353	-204799	-74894	-72296	-2079497

Note: P-values in parenthesis. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively.

Moreover, for all seven nationalities, λ is significantly different from one, except for Turkish immigrants. For the remaining nationalities, we can reject the null hypothesis that our model may be reduced to a standard non nested logit model. Furthermore, both scale factors μ_1 and μ_2 are positive and significantly differ from zero. This finding suggests that there is uncertainty in the choice of both the area and the location within the area so that we can exclude spatial concentration of immigrants in one district or municipality within the district. The scale factors strongly differ across nationalities: they are highest for French, Moroccan and Turkish immigrants and lower than average for Italians in both scenarios. For some nationalities (i.e. Moroccans and Turks), the scale factors are close to 0.5, implying that the variance of the random term at the area level is approximately the same as the variance of the random term at the municipal level.

With respect to the network effect, we find similar results compared to the multinomial logit model, though with some important exceptions. The own migrant stock as well as the average stock in neighboring municipalities becomes insignificant for some nationalities. The most striking discrepancy between the two models, however, concerns Italians for whom the estimated traditional network effect becomes insignificant, after controlling for other factors. The neighboring migrant stocks remain significant at the 5 percent level, though. Own network effects are strongest for French and Turkish immigrants, whereas the migrant stock at surrounding municipalities has the strongest effect for Italians.

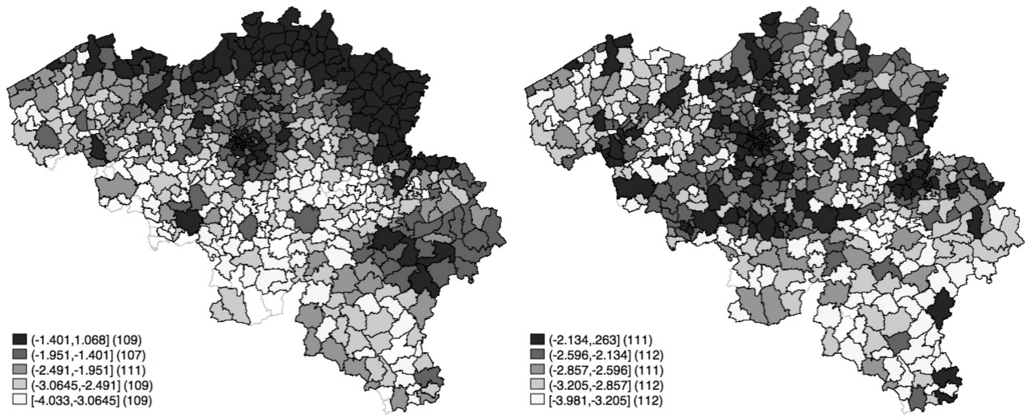
House prices now become positively significant for all immigrants from the neighboring countries. This suggests that immigrants from Western European origins tend to favor municipalities that are relatively more wealthy. For Moroccans and Poles, on the other hand, we find negative significant effects of house prices. The prices of apartments are generally only significant with the expected sign for Germans and Turks, and insignificant for the remaining nationalities. When significant, the coefficients of house and apartment transactions are generally positive, except for Italians. This confirms that immigrants favor municipalities where the acquisition of housing is relatively less challenging.[11]

[11] It might be argued that a large inflow of immigrants in a municipality might create pressure on the housing market, driving up housing prices and the number of transactions. In order to test

With respect to the unemployment rate, we mostly find negative significant effects, in line with our expectations. The effect is significant for German, Dutch and Turkish immigrants. For Italians, on the other hand, we find a significant positive effect, though only at the 5 percent significance level.

Finally, as they are too numerous to be tabulated, the location effects from the nested logit model are illustrated in Figure 4.7, for two representative cases, i.e. Dutch and Moroccan immigration.[12] The maps indicate to which municipalities immigrants are drawn once network effects and other time varying location determinants have been neutralized. For the Dutch case, we find important local effects in municipalities located along the Dutch border, in and around Brussels and in the South-East. In the Moroccan case, on the other hand, attractive municipalities are more spread and especially situated along a North-South line, from Antwerp to Charleroi through Brussels.

Figure 4.7: Local effects for Dutch and Moroccan immigrants



for potential reverse causality, we re-estimated the model using the first, second or third lag of housing prices. Though not reported here for brevity, the results appear robust to whether these variables are lagged or not. The results are available upon request from the authors.

[12]The location effects could not be estimated for a small number of municipalities, namely those that did not receive any migrant of a specific origin during the sample period.

4.5.2 Networks versus local effects

In this section we examine to what extent the current location pattern of immigrants in Belgium is determined by the genuine attractiveness of locations (captured by the time invariant location factors, from now on referred to as "local effects") relative to the network effect. In other words, we want to see which source of persistence is the most powerful. This question can be answered by decomposing the number of immigrants in each location into a part explained by the network effect, the local effect and a residual. This allows us to define the number of immigrants who would be choosing a certain location if there were no network (local) effects and to single out the direct consequence of network (local) effects. To calculate the immigrant rates predicted by the different models, let us rewrite the probability equations (4.6) and (4.8) by replacing $z_{i,t}$ and $z_{k,t}$ by their functional form in (4.32) and (4.33) and the parameters $\beta = (\beta_0,...,\beta_6)$, β_1^* and α_i by their estimated values . Specifically, the probability that a migrant chooses a certain location i at time t, i.e. $\hat{p}_{i,t}$, becomes

$$\hat{p}_{i,t} = \hat{p}_{i,t}^2 \hat{p}_{\kappa(i),t}^1 \tag{4.36}$$

$$\hat{p}_{i,t}^2 = \frac{\exp\left(\hat{b_1}(\ln s_{i,t-1}+1)+\hat{b_2}(\ln sn_{i,t-1}+1)+\Omega_{i,t}+\hat{a}_i^2\right)}{\sum_{j,\kappa(j)=k}\exp\left(\hat{b_1}(\ln s_{j,t-1}+1)+\hat{b_2}(\ln sn_{j,t-1}+1)+\Omega_{j,t}+\hat{a}_j^2\right)} \tag{4.37}$$

$$\hat{V}_{k,t} = \log\left(\sum_{j,\kappa(j)=k}\exp\left(\hat{b_1}(\ln s_{j,t-1}+1)+\hat{b_2}(\ln sn_{j,t-1}+1)+\Omega_{j,t}+\hat{a}_j^2\right)\right) \tag{4.38}$$

$$\hat{p}_{k,t}^1 = \frac{\exp\left(\hat{b_1^*}\ln u_{i,t}+\hat{a}_k^1+\hat{\lambda}\hat{V}_{k,t}\right)}{\sum_m \exp\left(\hat{b_1^*}\ln u_{m,t}+\hat{a}_m^1+\hat{\lambda}\hat{V}_{m,t}\right)} \tag{4.39}$$

with $\Omega_{i,t}$ the vector of all time varying location factors except network effects, namely

$$\Omega_{i,t} = \hat{b_3} \ln hp_{i,t} + \hat{b_4} \ln ap_{i,t} + \hat{b_5} \ln ht_{i,t} + \hat{b_6} \ln at_{i,t}. \tag{4.40}$$

If there were no network effects, the parameters $\hat{b_1}$ and $\hat{b_2}$ would be zero, so that the estimated probability without network effects becomes

$$\hat{p}'_{i,t} = \hat{p}^{2'}_{i,t} \hat{p}^{1'}_{\kappa(i),t} \tag{4.41}$$

$$\hat{p}^{2'}_{i,t} = \frac{\exp\left(\Omega_{i,t} + \hat{a}^2_i\right)}{\sum_{j,\kappa(j)=k} \exp\left(\Omega_{i,t} + \hat{a}^2_j\right)} \tag{4.42}$$

$$\hat{V}'_{k,t} = \log\left(\sum_{j,\kappa(j)=k} \exp\left(\Omega_{i,t} + \hat{a}^2_j\right)\right) \tag{4.43}$$

$$\hat{p}^{1'}_{k,t} = \frac{\exp\left(\hat{b}^*_1 \ln u_{i,t} + \hat{a}^1_k + \hat{\lambda}\hat{V}'_{k,t}\right)}{\sum_m \exp\left(\hat{b}^*_1 \ln u_{m,t} + \hat{a}^1_m + \hat{\lambda}\hat{V}'_{m,t}\right)}. \tag{4.44}$$

Without local effects, on the other hand, the parameters $\hat{a}^2_i$ and $\hat{a}^1_k$ are set to zero which results in the following estimated probabilities

$$\hat{p}''_{i,t} = \hat{p}^{2''}_{i,t} \hat{p}^{1''}_{\kappa(i),t} \tag{4.45}$$

$$\hat{p}^{2''}_{i,t} = \frac{\exp\left(\hat{b_1}(\ln s_{i,t-1} + 1) + \hat{b_2}(\ln sn_{i,t-1} + 1) + \Omega_{i,t}\right)}{\sum_{j,\kappa(j)=k} \exp\left(\hat{b_1}(\ln s_{j,t-1} + 1) + \hat{b_2}(\ln sn_{j,t-1} + 1) + \Omega_{j,t}\right)} \tag{4.46}$$

$$\hat{V}''_{k,t} = \log\left(\sum_{j,\kappa(j)=k} \exp\left(\hat{b_1}(\ln s_{j,t-1} + 1) + \hat{b_2}(\ln sn_{j,t-1} + 1) + \Omega_{j,t}\right)\right) \tag{4.47}$$

$$\hat{p}^{1''}_{k,t} = \frac{\exp\left(\hat{b}^*_1 \ln u_{i,t} + \hat{\lambda}\hat{V}''_{k,t}\right)}{\sum_m \exp\left(\hat{b}^*_1 \ln u_{m,t} + \hat{\lambda}\hat{V}''_{m,t}\right)}. \tag{4.48}$$

Subsequently, we calculate the number of migrants in each location as predicted by the complete model and the models without networks and local effects, respectively. Let $n_{.,t}$ denote the total number of foreigners (from a certain origin country) in Belgium at date t and $N_{i,t}$ the total population of location i at date t. Then $\tau_{i,t}$

is defined as the percentage of immigrants in the whole population in location i at date t. This gives

$$\hat{\tau}_{i,t} = 100 * \hat{n}_{i,t}/N_{i,t} \text{ with } \hat{n}_{i,t} = n_{.,t}\hat{p}_{i,t} \tag{4.49}$$

$$\hat{\tau}^{'}_{i,t} = 100 * \hat{n}^{'}_{i,t}/N_{i,t} \text{ with } \hat{n}^{'}_{i,t} = n_{.,t}\hat{p}^{'}_{i,t} \tag{4.50}$$

$$\hat{\tau}^{''}_{i,t} = 100 * \hat{n}^{''}_{i,t}/N_{i,t} \text{ with } \hat{n}^{''}_{i,t} = n_{.,t}\hat{p}^{''}_{i,t} \tag{4.51}$$

for the complete model, the model without network effects and the model without local factors, respectively. Hence, we can define three residual immigration rates, i.e. the difference between (i) the observed immigration rate and the one predicted by the complete model, i.e. $d_{i,t} = \tau^{obs}_{i,t} - \hat{\tau}_{i,t}$, (ii) the immigration rate predicted by the complete model and the model without network effects, i.e. $d^{'}_{i,t} = \hat{\tau}_{i,t} - \hat{\tau}'_{i,t}$, and (iii) the immigration rate predicted by the complete model and the model without local factors, i.e. $d^{''}_{i,t} = \hat{\tau}_{i,t} - \hat{\tau}''_{i,t}$.

The decomposition described above is carried out for each nationality separately and for the sum of these seven nationalities. Table 4.5 provides standard deviations for the observed immigration rates, $\tau^{obs}_{i,t}$, the immigration rates estimated from the complete model, $\hat{\tau}_{i,t}$, the immigration rates estimated from the model without network effects, $\hat{\tau}^{'}_{i,t}$, the immigration rates estimated from the model without local factors, $\hat{\tau}^{''}_{i,t}$, and three residual terms: the difference between the observed and estimated immigration rates from the complete model, $d_{i,t}$, between the immigration rates estimated with and without the network effect, $d^{'}_{i,t}$, as well as with and without the local factors, $d^{''}_{i,t}$. In addition, the table includes correlation coefficients between the estimated immigration rates from the complete model and the observed immigration rates, the immigration rates estimated without network effects and those estimated without local factors, respectively.

We find that the predictive power of the complete model is fairly high, except for

Italians. For the other nationalities, the estimated immigration rates predicted by the complete model are highly correlated (>0.7) with the observed immigration rates and their standard deviation is higher than that for the residual immigration rates.

Table 4.5: Decomposition of immigration rates

Immigration rate	DE	FRA	ITA	MOR	NL	POL	TUR	Total
								District level
Standard deviation of								
$\eta_{i,t}$	0.100	0.134	0.032	0.097	0.162	0.053	0.037	0.344
$\hat{\eta}_{i,t}$	0.052	0.133	0.042	0.099	0.165	0.054	0.036	0.349
$\hat{\eta}^{'}_{i,t}$	0.030	0.123	0.047	0.075	0.186	0.053	0.027	0.336
$\hat{\eta}^{''}_{i,t}$	0.054	0.088	0.035	0.047	0.077	0.038	0.021	0.274
$d_{i,t}$	0.066	0.092	0.046	0.063	0.112	0.041	0.022	0.261
$d^{'}_{i,t}$	0.040	0.022	0.019	0.044	0.045	0.009	0.026	0.114
$d^{''}_{i,t}$	0.046	0.153	0.059	0.106	0.189	0.064	0.037	0.457
Correlation between $\hat{\eta}_{i,t}$ *and*								
$\eta_{i,t}$	0.799	0.764	0.240	0.794	0.766	0.702	0.824	0.716
$\hat{\eta}^{'}_{i,t}$	0.630	0.989	0.911	0.908	0.973	0.986	0.698	0.945
$\hat{\eta}^{''}_{i,t}$	0.632	0.088	-0.135	0.066	-0.106	0.056	0.233	-0.064

Dropping network effects lowers the variance of estimated immigration rates, except for Italians and the Dutch. Apart from German and Turkish immigration, we find a strong correlation between estimated immigration rates from the complete model and the model without network effects. This finding indicates that networks play a more important role for Germans and Turks compared to other nationalities in our sample. Dropping location factors, on the other hand, clearly reduces the variance of the estimated immigration rates for all nationalities, except for German immigrants. Unsurprisingly, we also find very low correlations between immigrant rates estimated by the complete model and the model without location factors, except for German immigrants for whom the correlation remains

0.6 once local factors have been excluded.

These findings suggest that, except for German and Turkish immigrants, the role for network effects is small. Yet, the local effects seem to unambiguously dominate network effects for all nationalities in our sample.

4.5.3 The determinants of the local effects

Using the consistent estimates of the local effects from the first step, $\hat{\alpha}_i$, we can finally estimate the parameters of the time invariant location factors defined in (4.34). The model was first estimated using OLS in order to detect the presence of spatial autocorrelation in the local effects. The same row-normalized inverse distance spatial weight matrix, W, is used for both the spatial lag and the spatial error. OLS estimates and LM test statistics for the presence and structure of spatial autocorrelation can be found in Table 4.13. Specifically, the table reports five LM tests: ordinary and robust LM tests for the spatial lag model developed by Anselin (1988) and Kelejian and Robinson (1992) respectively; ordinary and robust LM tests for the spatial error model developed by Burridge (1981) and Kelejian and Robinson (1992) respectively; and an LM test for the joint model incorporating both a spatial lag and a spatial error term. The test statistics always confirm the presence of spatial correlation in the residuals. They sometimes confirm the presence of a spatial lag in the dependent variable. Consequently, we proceed by estimating an SDM model and report Wald and Likelihood Ratio (LR) tests to see whether the SDM can be simplified to a SAR or SEM model. The test statistics, presented in in the lower panel of Table 4.13, reveal that these hypotheses can be rejected at the 1 percent significance level for all nationalities. As such, the model is estimated using maximum likelihood techniques that account for the presence of a spatial lag in both the local effects and the explanatory variables. This spatial structure has the important advantage that it controls for any omitted variables that exhibits spatial dependence.

Table 4.14 displays results obtained with local effects estimated from the nested model. First of all, we find evidence for a strong and significant spatial lag in the local effects. Yet, an implication of accounting for spatial dependence is that the estimated parameters cannot be interpreted as usual in a standard linear regression model. Cross-country interactions prevent the parameter estimates from being interpreted as the simple partial derivatives of the dependent variable with respect to the explanatory variables (see Anselin and Le Gallo, 2006; Kelejian et al., 2006; LeSage and Pace, 2009). LeSage and Pace (2009) suggest three summary measures of the varying impacts of changes in an explanatory variable across locations:

(i) average direct impact: the impact from changes in the ith observation of variable k on location i, averaged over all locations

(ii) average indirect impact: the effect of changes in the ith observation of variable k on location j ($\neq i$), averaged over all locations, capturing the spillover effects of a change in location i on all other locations

(iii) average total impact: the sum of the previous two, reflecting how changes in a single location potentially influence all observations.

The direct effects correspond the most to the typical regression coefficient interpretation that represents the average response of the dependent variable to independent variables over the sample of observations. The main difference is that the direct effect takes into account effects from changes in location i to location j and back to location i itself. Because they allow for an explicit comparison with parameter estimates from other studies on migration determinants in the literature, we will concentrate primarily on the average direct effects, although we also briefly comment upon the indirect effects. The direct and indirect effects estimates can be found in Tables 4.6 and 4.7, respectively. The latter are however far less significant than their direct counterparts, except for French immigrants and the immigration population as a whole. For these subsets of immigrants, the spatial lag is close to one, resulting in fairly large indirect effects estimates. Given that the final step in the estimation procedure is rather explorative, these results should be interpreted with caution. This final step is however explorative in nature and does not aim to provide an in-depth analysis of the role played by each of the location characteristics in shaping the geographical spread of immigrants, but rather serves as an indication of the relative importance of other factors at work besides network effects.

With a few exceptions, our findings are in line with the predictions of the theoretical model. First of all, surface and population density appear to be the most robust location determinants for immigrants. In line with our expectations, the estimated direct effects are always positive and highly significant. Indirectly, we only find a positive impact for the French.

As far as concerns the proxies for the migration cost, our results confirm that immigrants from neighboring countries prefer locations close to the border of their home country. Specifically, the effects are always negative except for Poles, but we find significant direct effects only for French, Dutch and Italian immigrants. Minimal distance to Brussels appears insignificant for all nationalities, with the exception of a marginally significant indirect effect for the French and the immigrant population as a whole. The former thus prefer municipalities located closer to Brussels, in particular along the French border.

The relative number of hospitals has a predominant positive effect on migration. The results for the number of secondary schools as a share of the local population are however more ambiguous. Although the direct effect is significantly positive for Italian and Turkish immigrants, we find a significant negative impact for

Table 4.6: Direct effects estimates, nested logit model - SDM

Dependent variable: $\hat{a}_i$								Sample period: 1994-2007
	DE	FR	IT	MA	NL	PL	TR	TOT
$\ln sf_i$	0.683***	0.526***	0.665***	0.585***	0.614***	0.771***	0.639***	0.351
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.108)
$\ln pd_i$	0.623***	0.879***	0.856***	0.762***	0.531***	0.802***	0.819***	0.912***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\ln dbo_i$	−0.013	−0.041***	−0.044***	−0.003	−0.060***	0.006	−0.001	−0.102***
	(0.053)	(0.000)	(0.000)	(0.589)	(0.000)	(0.407)	(0.869)	(0.000)
$\ln dbr_i$	0.003	0.039	−0.076	−0.004	−0.075	0.065	−0.054	−0.015
	(0.948)	(0.600)	(0.34)	(0.928)	(0.288)	(0.301)	(0.273)	(0.831)
$\ln ho_i$	0.168**	0.947***	0.122	0.046	−0.048	0.229***	0.097*	0.886***
	(0.013)	(0.000)	(0.156)	(0.335)	(0.618)	(0.005)	(0.058)	(0.004)
$\ln sc_i$	−0.032	−0.539***	0.103*	0.052	0.032	0.023	0.070**	−0.686***
	(0.476)	(0.000)	(0.089)	(0.108)	(0.628)	(0.680)	(0.029)	(0.002)
$\ln sp_i$	0.021**	0.009	0.007	0.005	0.092***	−0.011*	0.019***	−0.017**
	(0.011)	(0.431)	(0.418)	(0.533)	(0.000)	(0.080)	(0.000)	(0.013)
$\ln mw_i$	−0.002	0.039***	0.011	0.001	0.014	−0.011	0.005	0.193***
	(0.747)	(0.002)	(0.284)	(0.883)	(0.176)	(0.183)	(0.479)	(0.000)
$\ln to_i$	0.018***	0.005	0.020***	0.005	0.031***	0.012**	0.006	0.060***
	(0.000)	(0.442)	(0.003)	(0.118)	(0.000)	(0.031)	(0.155)	(0.000)
$\ln ur_i$	0.050	−0.095	0.136**	0.013	0.004	−0.067	−0.024	−0.040
	(0.300)	(0.139)	(0.039)	(0.717)	(0.940)	(0.236)	(0.541)	(0.727)
cl_i	−0.402	0.142	0.000	−0.080	1.632***	0.000	0.000	0.000
	(0.170)	(0.423)	(0.000)	(0.511)	(0.000)	(0.000)	(0.000)	(0.000)

Note: P-values in parenthesis are calculated using simulated standard errors based on 1000 bootstrap samples. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively.

the French and the immigrant population as a whole (both in direct and indirect terms). The effect for sport clubs, on the other hand, is often significant with the expected sign, except directly for Polish immigrants. Apart from the number of secondary schools, these findings confirm the hypothesis that public amenities may act as a strong pull for immigrants, once other location factors have been taken into account.

Also the highway network mostly appears with a positive sign, though only significant for French immigrants and indirectly for the Dutch. Touristic attractiveness,

Table 4.7: Indirect effects estimates, nested logit model - SDM

Dependent variable: $\hat{a}_i$ Sample period: 1994-2007

	DE	FR	IT	MA	NL	PL	TR	TOT
$\ln sf_i$	−24.409	220.608**	−175.712	17.542	−48.872	23.451	7.563	24.86
	(0.657)	(0.032)	(0.339)	(0.586)	(0.593)	(0.625)	(0.979)	(0.804)
$\ln pd_i$	3.432	417.257***	−241.146	40.247	−58.975	117.929	−0.462	209.339*
	(0.959)	(0.003)	(0.337)	(0.480)	(0.559)	(0.261)	(0.999)	(0.068)
$\ln dbo_i$	−8.385	−39.915***	−8.495	−2.817	−19.908*	−1.175	−0.886	−42.425***
	(0.319)	(0.001)	(0.376)	(0.491)	(0.072)	(0.797)	(0.952)	(0.000)
$\ln dbr_i$	13.617	−46.553*	−60.845	−2.625	10.328	−10.212	−14.530	−36.030*
	(0.449)	(0.053)	(0.311)	(0.718)	(0.504)	(0.453)	(0.956)	(0.054)
$\ln ho_i$	74.892	871.193***	−26.703	27.918	−29.792	87.335	−16.896	392.577***
	(0.411)	(0.000)	(0.778)	(0.516)	(0.785)	(0.336)	(0.973)	(0.007)
$\ln sc_i$	−53.002	−483.361***	−30.372	12.047	−4.434	29.475	51.430	−290.952***
	(0.406)	(0.001)	(0.654)	(0.643)	(0.956)	(0.574)	(0.968)	(0.006)
$\ln sp_i$	−5.518	0.528	−1.051	1.357	21.659	−2.407	0.870	2.334
	(0.296)	(0.952)	(0.689)	(0.639)	(0.228)	(0.323)	(0.969)	(0.421)
$\ln mw_i$	5.699	20.200	6.119	0.671	49.419**	−6.741	9.745	94.578***
	(0.542)	(0.126)	(0.614)	(0.846)	(0.040)	(0.458)	(0.968)	(0.000)
$\ln to_i$	0.986	7.983	5.808	−1.774	10.126	6.907	−0.696	30.339***
	(0.789)	(0.217)	(0.394)	(0.547)	(0.181)	(0.260)	(0.968)	(0.000)
$\ln ur_i$	−28.925	−111.771*	102.933	−34.060	45.154	−87.583	−32.616	−9.498
	(0.522)	(0.075)	(0.371)	(0.452)	(0.419)	(0.238)	(0.972)	(0.873)
cl_i	250.004	−109.302	0.000	−14.364	275.763	0.000	0.000	0.000
	(0.312)	(0.344)	(0.000)	(0.700)	(0.224)	(0.000)	(0.000)	(0.000)

Note: *P*-values in parenthesis are calculated using simulated standard errors based on 1000 bootstrap samples. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively.

measured by hotel occupancy, nonetheless, plays an unambiguous positive role in attracting new immigrants. Besides actual touristic attractiveness, this variable might also capture other characteristics of the municipality which add to its general appeal. The morphological urbanization rate is positively significant for Italians and indirectly significant for the French with the opposite sign. This is in line with the noticeable concentration of French immigrants in some of the more rural regions in Wallonia. The presence of a common language, finally, is only significant for Dutch immigrants with the expected sign.

4.6 Conclusions

This chapter analyzes migratory streams to Belgian municipalities between 1990-2007. Despite the renewed attention for the migration topic in the literature of the last two decades, the dynamics in the spatial repartition of immigrants remain poorly understood. For many European countries, their choice for a specific location within the destination country has not yet been explored, mainly because the required data has not been available. To fill this apparent gap in the literature, this chapter provides a descriptive analysis of the spatial distribution of immigrants in Belgium and empirically investigates their location dynamics. The Belgian population register constitutes a rich and unique database of both migrant inflows and stocks with a detailed breakdown by nationality and age cohort, which allows us to distinguish the immigrants of working age.

Specifically, we aim at separating the network effect, captured by the number of previous arrivals, from other location-specific characteristics such as local labor or housing market conditions and the presence of public amenities. We expect labor and housing market variables to operate on different levels and develop a nested logit model of location choice in which an immigrant first chooses a broad area, roughly corresponding to a labor market, and subsequently chooses a municipality within this area.

Our evidence suggests that this is a valid assumption and that immigrants' behavior is consistent with random utility maximization for all nationalities. Although existing social networks usually act as a significant pull towards newcomers, both in the municipality itself and in those surrounding it, we find that the spatial repartition of Belgian immigrants is predominantly driven by location-specific characteristics such as housing and labor market variables.

A decomposition of predicted immigration rates reveals that the predictive power of our nested logit model is fairly high. We find that the genuine attractiveness of municipalities typically dominates the positive influence of social networks.

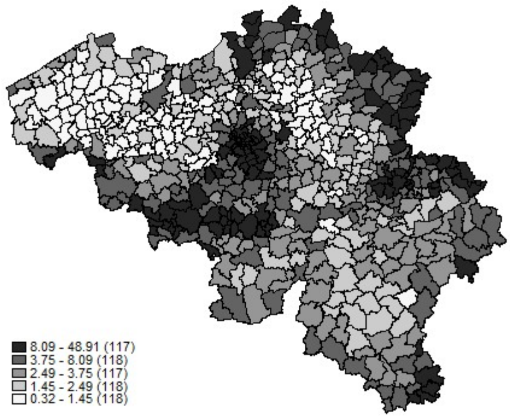
Finally, we estimate the parameters of the time invariant location determinants in our empirical model. We do not a priori assume a specific structure for spatial dependence in the local effects, but rely on a series of LM, Wald and LR tests to select the most appropriate specification. The test results reveal that a spatial lag for both the dependent and explanatory variables should be included in the regression. As such, we estimate an SDM model for the determinants of the local effects. The latter are found to vary by nationality, as expected, but with some noticeable parallels. The distance to the nearest border, for instance, is a significant determinant for immigrants from neighboring countries, as we would expect from the strong concentration of Dutch, French and German immigrants along the border of their origin country. But also the presence of public amenities and the municipality's touristic attractiveness act as a strong pull for immigrants.

In sum, our evidence suggests that the location choice of immigrants in Belgium is primarily determined by housing and labor market variables which vary in time, but also the genuine appeal of municipalities captured by the presence of public amenities and its touristic allure plays an important role in shaping the spatial repartition of immigrants.

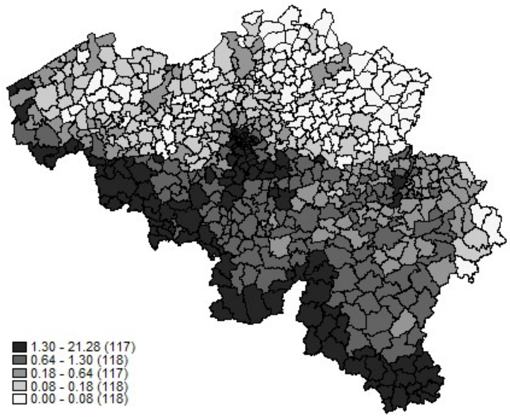
4.7 Appendix

4.7.1 Figures

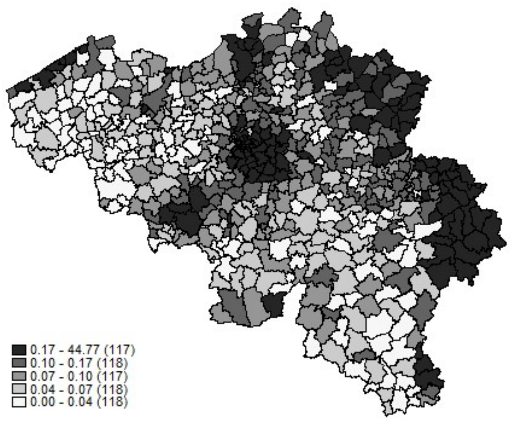
Figure 4.8: Total migrant stock as a share of the population by origin, 2007



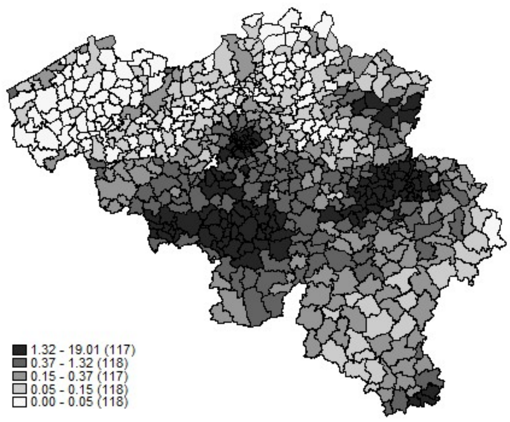
(a) All origins



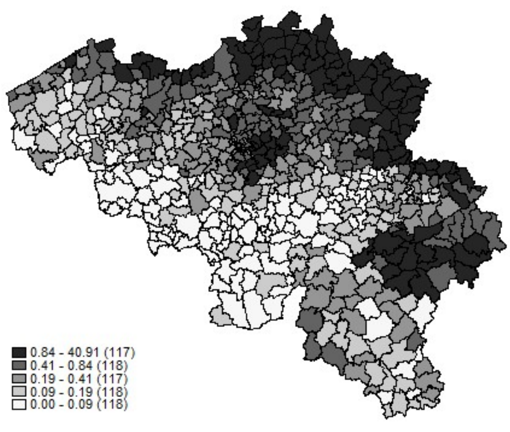
(b) France



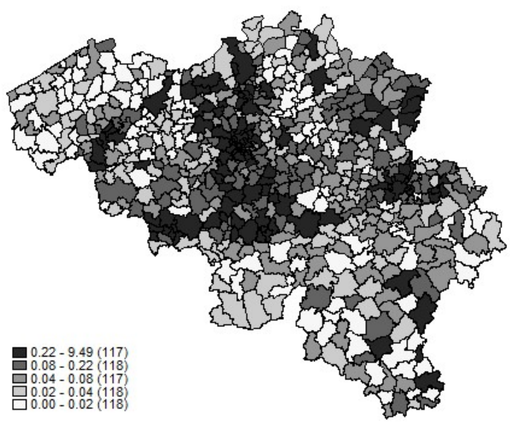
(c) Germany



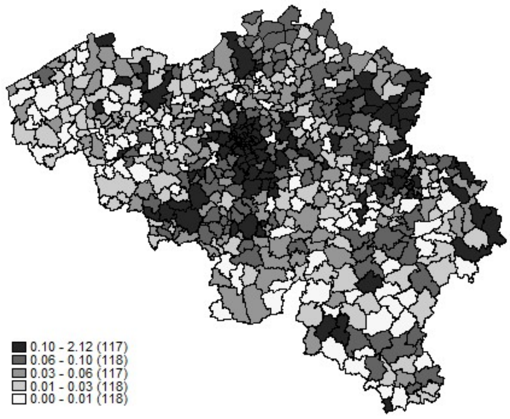
(d) Italy



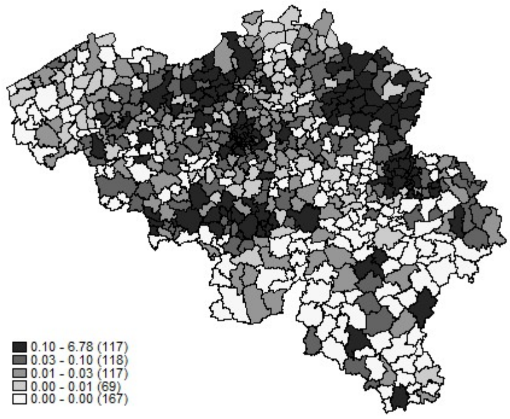
(e) Netherlands



(f) Morocco

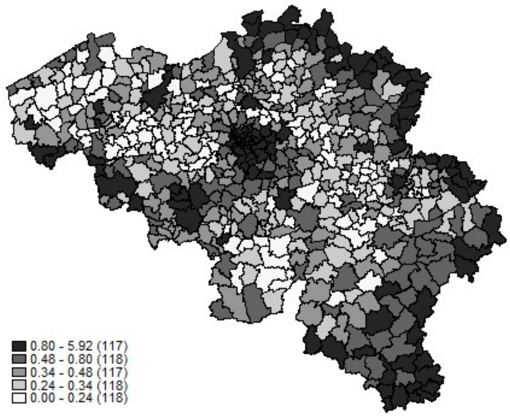


(h) Poland

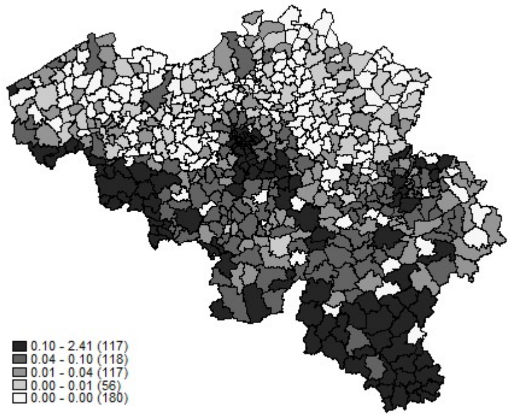


(i) Turkey

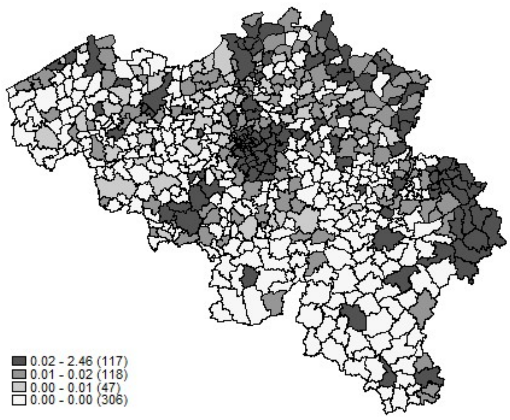
Figure 4.9: Total immigrant flow as a share of the population by origin, 2007



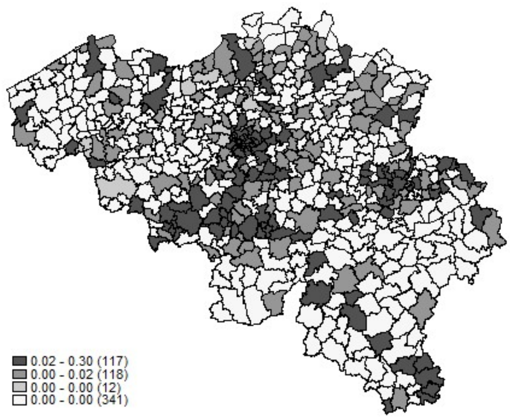
(a) All origins



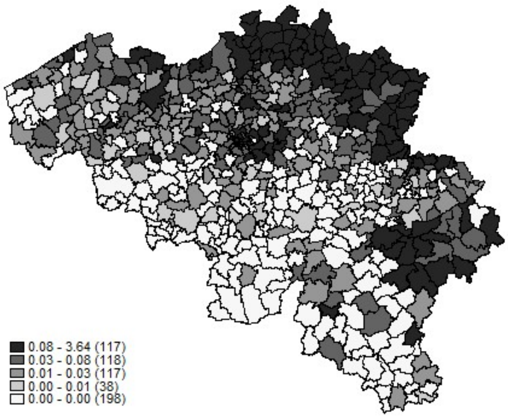
(b) France



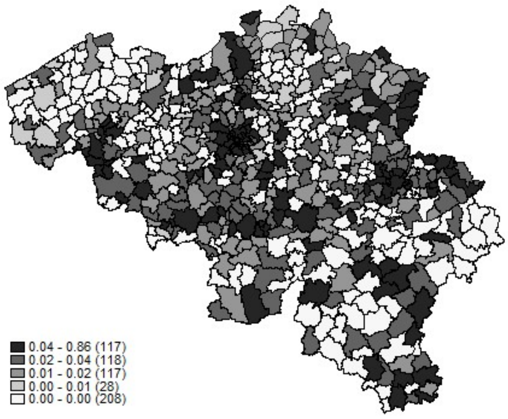
(c) Germany



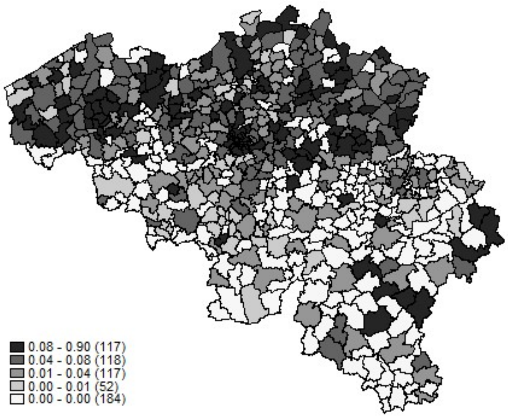
(d) Italy



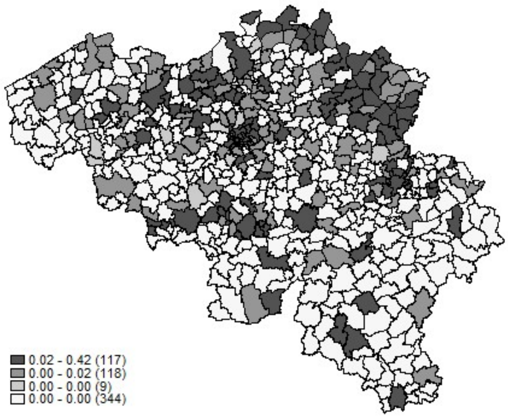
(f) Netherlands



(g) Morocco

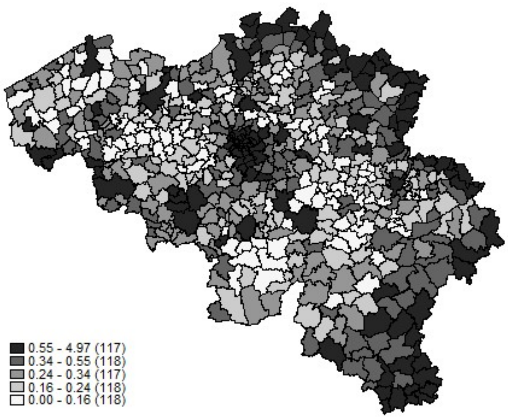


(h) Poland

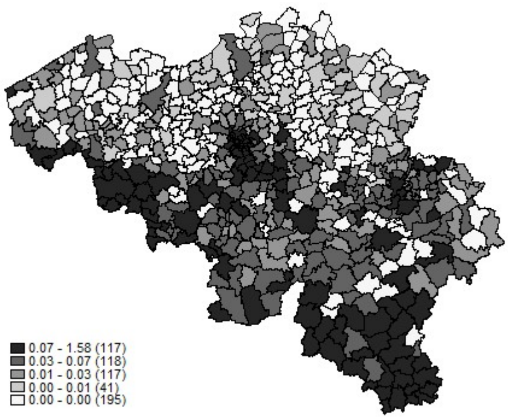


(i) Turkey

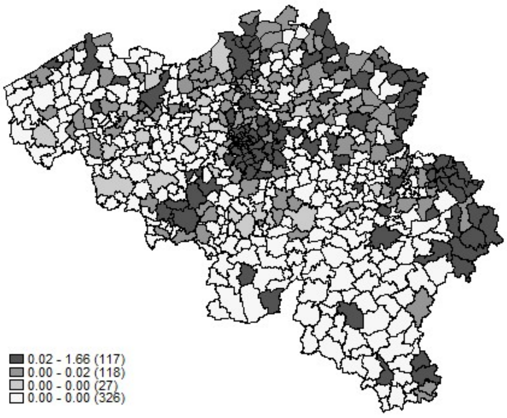
Figure 4.10: Active immigrant flow as a share of the population by origin, 2007



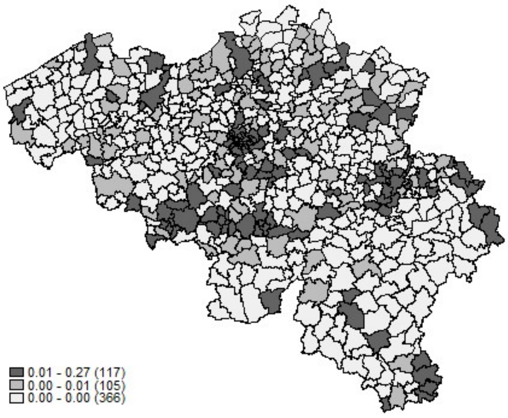
(a) All origins



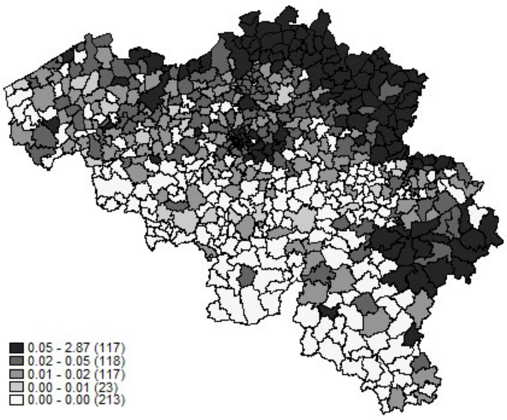
(b) France



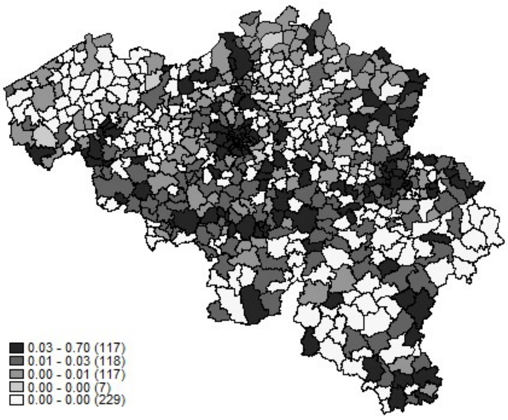
(d) Germany



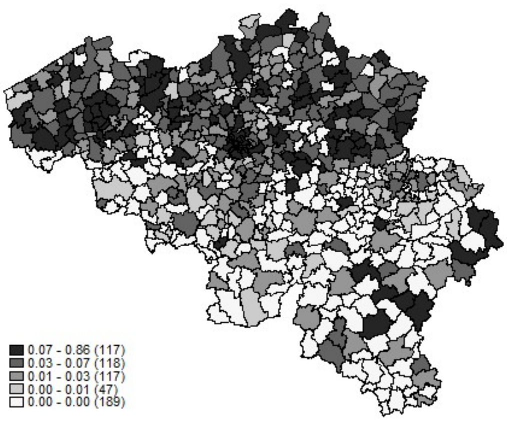
(e) Italy



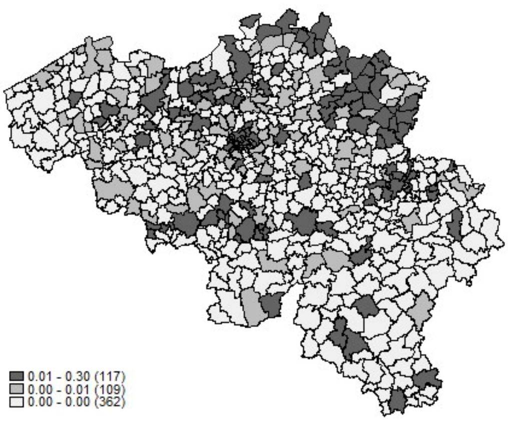
(f) Netherlands



(g) Morocco



(h) Poland



(i) Turkey

4.7.2 Tables

Table 4.8: Total (active and retired) migrant flows by country of origin 1990-2007

	FR	DE	IT	MA	NL	PL	TR	TOT	Sum	Share
1990	6011	2868	2643	2645	5923	776	2446	23312	62660	37.20
1991	5799	2695	2601	3443	6207	524	2900	24169	67460	35.83
1992	5912	2818	2581	3307	6633	560	2717	24528	66763	36.74
1993	5988	3013	2796	3358	6667	713	2514	25049	63749	39.29
1994	6150	3063	2754	4768	6477	793	3573	27578	66147	41.69
1995	6236	3132	2557	3596	6486	800	2520	25327	62950	40.23
1996	6579	3189	2731	4007	7834	946	2491	27777	61521	45.15
1997	7022	3114	2767	3880	6287	1063	1436	25569	58849	43.45
1998	7386	3206	2503	4327	6242	1118	2447	27229	61266	44.44
1999	7933	3070	2603	4936	6201	1151	2126	28020	68466	40.93
2000	8108	3037	2600	5667	7178	1134	2812	30536	68616	44.50
2001	8040	2884	2439	7072	8167	2928	2982	34512	77584	44.48
2002	8135	2966	2310	8495	8404	2427	3872	36609	82654	44.29
2003	8191	2942	2293	8444	8547	2086	3828	36331	81913	44.35
2004	9521	3308	2301	8014	8789	3481	3234	38648	85378	45.27
2005	10378	3250	2464	7106	10109	4816	3387	41510	90364	45.94
2006	11570	3290	2613	7488	11488	6694	2999	46142	96290	47.92
2007	12269	3385	2708	7831	11370	9393	3180	50136	106576	47.04
'90-'07	141228	55230	46264	98384	139009	41403	51464	572982	1329206	

Notes: Authors' calculations based on data from the Belgian Statistics Office. *TOT* reflects the sum of migrant stocks from the origin countries in our sample whereas*sum* denotes the total immigrant stock in Belgium, regardless of the country of origin. *Share* then captures the share of immigrant stocks from our sample of origin countries in the total immigrant stock, or the percentage of the total immigrant stock that is represented in our sample. *Growth* denotes the percentage change in migrant stocks between 1989 and 2006.

Table 4.9: Active migrant flows by country of origin 1990-2007

	FR	DE	IT	MA	NL	PL	TR	TOT	Sum	Share
1990	4171	2109	1700	1937	4271	617	1461	42450	16266	38.32
1991	3994	2014	1718	2458	4494	414	1777	45790	16869	36.84
1992	4195	2091	1694	2350	4814	441	1639	45919	17224	37.51
1993	4268	2231	1901	2522	4811	550	1571	44364	17854	40.24
1994	4356	2249	1860	3617	4784	621	2248	45228	20253	44.78
1995	4420	2272	1814	2715	4924	620	1545	43111	18678	43.33
1996	4630	2322	1952	3039	5875	720	1502	42686	20383	47.75
1997	5129	2313	2032	3088	4699	845	893	41977	19448	46.33
1998	5359	2329	1860	3351	4678	907	1525	43431	20473	47.14
1999	5810	2277	1948	3934	4703	918	1379	48335	21641	44.77
2000	6086	2236	1919	4289	5317	888	1765	48983	23253	47.47
2001	5993	2136	1836	5694	6121	2109	1962	55813	26948	48.28
2002	6128	2218	1805	6433	6287	1898	2559	59603	28423	47.69
2003	6154	2194	1774	5987	6267	1699	2500	58387	27753	47.53
2004	7037	2502	1828	5981	6404	2826	2232	61393	30505	49.69
2005	8585	2636	1999	5963	7686	4017	2783	64963	36348	100.00
2006	9559	2611	2138	6253	8500	5690	2606	70080	40600	100.00
2007	9100	2532	2131	6065	7922	7930	2494	78655	44668	56.79
’90-’07	104974	41272	33909	75676	102557	33710	34441	883073	447587	

Notes: see Table 4.8.

Table 4.10: Total (active and retired) migrant stocks by country of origin 1989-2006

	FR	DE	IT	MA	NL	PL	TR	TOT	Sum	Share
1989	91508	26713	241043	135467	60549	4714	79460	639454	830344	77.01
1990	92277	26973	240511	138422	62412	4693	81775	647063	842140	76.84
1991	94336	28080	241223	141663	65294	4943	84935	660474	863433	76.49
1992	94919	28518	240069	145602	67729	4825	88365	670027	877896	76.32
1993	95229	29327	217596	144993	69730	4817	88269	649961	862964	75.32
1994	97199	30250	216079	145363	72610	4908	88302	654711	871514	75.12
1995	98804	31046	213590	143969	75047	5217	85981	653654	885970	73.78
1996	100168	31823	210720	140304	77175	5376	81744	647310	872676	74.18
1997	101825	32706	208275	138253	80615	5722	78532	645928	866959	74.51
1998	103638	33326	205851	132838	82320	6037	73818	637828	859782	74.18
1999	105185	34051	202717	125087	84234	6322	70704	628300	859227	73.12
2000	107322	34328	200354	121991	85783	6755	69185	625718	862773	72.52
2001	109398	34587	195658	106828	88831	6936	56174	598412	829170	72.17
2002	111225	34668	190866	90646	92582	8891	45866	574744	811484	70.83
2003	113120	35096	187092	83633	96663	10357	42562	568523	812752	69.95
2004	115025	35540	183091	81766	100718	11574	41336	569050	819683	69.42
2005	117431	36334	179080	81285	104997	14000	39886	573013	826917	69.30
2006	120698	37014	175561	80613	110513	18032	39665	582096	863222	67.43
’90-’07	1869307	580380	3749376	2178723	1477802	134119	1236559	11226266	15318906	
Growth	31.90	38.56	-27.17	-40.49	82.52	282.52	-50.08	-8.97	3.96	

Notes: see Table 4.8.

Table 4.11: Descriptive statistics districts

	Total (active and retired)				Active			
Variable	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
Flows								
TOT	1717	3719	34	34992	1141	2613	14	26806
DE	71	189	0	1312	53	143	0	908
FR	182	525	0	5232	136	416	0	4479
IT	60	148	0	1071	44	114	0	934
MA	127	458	0	4376	98	353	0	3349
NL	180	395	0	2918	133	291	0	2154
PL	53	238	0	3464	44	190	0	2768
TR	66	139	0	1068	44	96	0	748
Ln $(s_{i,t-1}+1)$								
TOT	8.79	1.48	4.98	12.50	8.79	1.48	4.98	12.50
DE	5.09	1.63	1.61	9.49	5.09	1.63	1.61	9.49
FR	6.74	1.44	3.76	10.64	6.74	1.44	3.76	10.64
IT	6.41	2.27	0.00	10.96	6.41	2.27	0.00	10.96
MA	5.99	1.80	3.14	10.03	5.99	1.80	3.14	10.03
NL	5.61	2.25	0.00	11.27	5.61	2.25	0.00	11.27
PL	3.92	1.50	0.00	9.19	3.92	1.50	0.00	9.19
TR	5.13	2.48	0.00	9.99	5.13	2.48	0.00	9.99
Ln flows								
TOT	11.19	0.17	10.98	11.58	10.78	0.18	10.50	11.27
DE	8.03	0.06	7.90	8.13	7.73	0.07	7.61	7.88
FR	8.94	0.23	8.67	9.41	8.63	0.27	8.29	9.17
IT	7.85	0.06	7.74	7.94	7.54	0.07	7.43	7.67
MA	8.54	0.37	7.88	9.05	8.27	0.39	7.57	8.77
NL	8.93	0.21	8.69	9.35	8.63	0.20	8.36	9.05
PL	7.34	0.85	6.26	9.15	7.11	0.87	6.03	8.98
TR	7.93	0.23	7.27	8.26	7.52	0.29	6.79	7.93

Note: the sample includes 43 districts and 18 years, thus 774 observations.

Table 4.12: Descriptive statistics municipalities

	All (active and retired)				Active			
Variable	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
Flows								
TOT	126	413	0	10001	83	294	0	7718
DE	5	22	0	424	4	17	0	301
FR	13	56	0	1302	10	43	0	1168
IT	4	16	0	241	3	13	0	218
MA	9	55	0	1228	7	42	0	909
NL	13	54	0	1980	10	41	0	1466
PL	4	27	0	1459	3	22	0	1149
TR	5	25	0	539	3	17	0	362
Ln $(s_{i,t-1}+1)$								
TOT	5.80	1.56	0.69	10.94	5.80	1.56	0.69	10.94
DE	2.29	1.59	0.00	8.43	2.29	1.59	0.00	8.43
FR	3.54	1.75	0.00	8.88	3.54	1.75	0.00	8.88
IT	3.30	2.18	0.00	10.06	3.30	2.18	0.00	10.06
MA	2.12	2.15	0.00	9.98	2.12	2.15	0.00	9.98
NL	3.30	1.79	0.00	9.05	3.30	1.79	0.00	9.05
PL	1.26	1.30	0.00	7.56	1.26	1.30	0.00	7.56
TR	1.53	2.08	0.00	9.20	1.53	2.08	0.00	9.20
Ln flows								
TOT	11.19	0.17	10.98	11.58	10.78	0.18	10.50	11.27
DE	8.03	0.06	7.90	8.13	7.73	0.07	7.61	7.88
FR	8.94	0.23	8.67	9.41	8.63	0.27	8.29	9.17
IT	7.85	0.06	7.74	7.94	7.54	0.07	7.43	7.67
MA	8.54	0.37	7.88	9.05	8.27	0.39	7.57	8.77
NL	8.93	0.21	8.69	9.35	8.63	0.20	8.36	9.05
PL	7.34	0.85	6.26	9.15	7.11	0.87	6.03	8.98
TR	7.93	0.23	7.27	8.26	7.52	0.29	6.79	7.93

Note: the sample includes 588 municipalities and 18 years, thus 10584 observations.

Table 4.13: Second step estimates, nested logit model - OLS

Dependent variable: $\hat{a}_i$ — Sample period: 1994-2007

	DE	FR	IT	MA	NL	PL	TR	TOT
Intercept	-2.197^{***}	0.716	-4.794^{***}	-0.955^{**}	-5.35^{***}	0.142	-1.734^{***}	2.963^{***}
	(0.000)	(0.337)	(0.000)	(0.017)	(0.000)	(0.795)	(0.000)	(0.000)
$\ln sf_i$	0.654^{***}	0.321^{***}	0.833^{***}	0.55^{***}	0.542^{***}	0.68^{***}	0.657^{***}	0.158^{**}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.034)
$\ln pd_i$	0.59^{***}	0.631^{***}	0.763^{***}	0.761^{***}	0.534^{***}	0.74^{***}	0.777^{***}	0.599^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\ln dbo_i$	-0.022^{***}	-0.032^{***}	-0.034^{***}	-0.008^{*}	-0.076^{***}	0	-0.01^{*}	-0.049^{***}
	(0.000)	(0.000)	(0.000)	(0.063)	(0.000)	(0.956)	(0.064)	(0.000)
$\ln dbr_i$	0.008	-0.32^{***}	0.061	-0.074^{***}	0.043	-0.157^{***}	0.003	-0.303^{***}
	(0.819)	(0.000)	(0.162)	(0.002)	(0.36)	(0.000)	(0.892)	(0.000)
$\ln ho_i$	0.126^{**}	0.187^{**}	0.209^{**}	0.048	-0.102	0.139^{**}	0.123^{**}	0.004
	(0.028)	(0.022)	(0.02)	(0.273)	(0.263)	(0.033)	(0.016)	(0.958)
$\ln sc_i$	0.036	-0.086^{*}	0.255^{***}	0.048^{*}	0.02	0.045	0.043	-0.119^{**}
	(0.311)	(0.085)	(0.000)	(0.071)	(0.725)	(0.252)	(0.162)	(0.02)
$\ln sp_i$	0.007	0.042^{***}	-0.001	0.023^{***}	0.188^{***}	-0.008^{**}	0.018^{***}	0.008^{*}
	(0.109)	(0.000)	(0.905)	(0.000)	(0.000)	(0.021)	(0.000)	(0.085)
$\ln mw_i$	0.005	0.036^{***}	0.003	0.007	0.016	-0.009	0.008	0.03^{***}
	(0.502)	(0.001)	(0.769)	(0.191)	(0.178)	(0.262)	(0.207)	(0.004)
$\ln to_i$	0.022^{***}	-0.004	0.027^{***}	0.012^{***}	0.049^{***}	0.02^{***}	0.011^{***}	0.014^{**}
	(0.000)	(0.472)	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)	(0.023)
$\ln ur_i$	0.045	-0.104^{*}	0.165^{**}	-0.011	0.003	-0.07	-0.03	-0.099
	(0.337)	(0.096)	(0.023)	(0.746)	(0.962)	(0.168)	(0.468)	(0.126)
cl_i	0.45^{**}	0.337^{**}		0.05	3.022^{***}			
	(0.017)	(0.02)		(0.517)	(0.000)			

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	DE	FR	IT	MA	NL	PL	TR	TOT
Adj R^2	0.564	0.507	0.513	0.771	0.531	0.565	0.668	0.525
LM spatial lag	2.103	378.031***	177.324***	3.938**	433.468***	55.742***	0.910	1028.932***
Prob $> \chi(1)$	(0.147)	(0.000)	(0.000)	(0.047)	(0.000)	(0.000)	(0.34)	(0.000)
LM spatial lag (robust)	3.690*	32.116***	47.000	21.134***	34.540	0.568	10.777***	17.493***
Prob $> \chi(1)$	(0.055)	(0.000)	(0.000)	(0.000)	(0.000)	(0.451)	(0.001)	(0.000)
LM spatial error	30.758***	512.72***	211.725***	130.852***	1678.934***	106.291***	25.954***	1951.902***
Prob $> \chi(1)$	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LM spatial error	32.345***	166.805***	81.401***	148.048***	1280.007***	51.116***	35.821***	940.463***
Prob $> \chi(1)$	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LM spatial lag and error	34.449***	544.836***	258.725***	151.986***	1713.475***	106.859***	36.731***	1969.395***
Prob $> \chi(2)$	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Wald SDM vs SAR	−1415.200***	5510.400***	195.232***	11110.000***	−13352.000***	2618.800***	52.611***	−34277.000***
Prob $> \chi(7)$	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LR SDM vs SAR	46.844***	118.695***	79.304***	113.155***	200.756***	58.734***	48.713***	184.761***
Prob $> \chi(7)$	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Wald SDM vs SEM	−931.291***	5050.700***	142.142***	37403.000***	−858.869***	−16517.000***	63.027***	−4879.500***
Prob $> \chi(7)$	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LR SDM vs SEM	33.351***	140.130***	99.554***	77.128***	164.002***	56.211***	37.593***	200.033***
Prob $> \chi(7)$	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note: *P*-values in parenthesis. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively.

Table 4.14: Second step estimates, nested logit model - SDM

Dependent variable: $\hat{a}_i$ Sample period: 1994-2007

	DE	FR	IT	MA	NL	PL	TR	TOT
Intercept	-3.183^{**}	-9.729^{**}	7.551^{***}	-5.638^{***}	-9.937^{***}	-3.625	-3.035^{***}	8.551
	(0.029)	(0.025)	(0.000)	(0.000)	(0.000)	(0.142)	(0.004)	(0.279)
$\ln sf_i$	0.693^{***}	0.341^{***}	0.726^{***}	0.573^{***}	0.638^{***}	0.755^{***}	0.639^{***}	0.301^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\ln pd_i$	0.617^{***}	0.529^{***}	0.940^{***}	0.732^{***}	0.563^{***}	0.715^{***}	0.821^{***}	0.489^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\ln dbo_i$	-0.010	-0.007	-0.041^{***}	-0.001	-0.050^{***}	0.007	-0.001	-0.017^{**}
	(0.183)	(0.367)	(0.000)	(0.874)	(0.000)	(0.351)	(0.884)	(0.029)
$\ln dbr_i$	-0.001	0.076	-0.048	-0.002	-0.085	0.071	-0.053	0.060
	(0.992)	(0.284)	(0.538)	(0.957)	(0.222)	(0.255)	(0.268)	(0.359)
$\ln ho_i$	0.133^{**}	0.225^{***}	0.133^{*}	0.027	-0.033	0.163^{***}	0.096^{*}	0.095
	(0.017)	(0.001)	(0.095)	(0.502)	(0.632)	(0.008)	(0.056)	(0.129)
$\ln sc_i$	-0.007	-0.140^{***}	0.116^{**}	0.044^{*}	0.037	0.003	0.066^{**}	-0.100^{**}
	(0.844)	(0.001)	(0.025)	(0.088)	(0.408)	(0.944)	(0.035)	(0.013)
$\ln sp_i$	0.023^{***}	0.009	0.008	0.003	0.083^{***}	-0.009	0.019^{***}	-0.021^{***}
	(0.005)	(0.489)	(0.366)	(0.640)	(0.001)	(0.161)	(0.001)	(0.001)
$\ln mw_i$	-0.005	0.023^{***}	0.009	0.001	-0.011	-0.007	0.004	0.002
	(0.467)	(0.009)	(0.377)	(0.917)	(0.230)	(0.385)	(0.490)	(0.771)
$\ln to_i$	0.018^{***}	-0.001	0.018^{***}	0.007	0.025^{***}	0.006	0.006	-0.001
	(0.000)	(0.844)	(0.008)	(0.045)	(0.000)	(0.203)	(0.163)	(0.817)
$\ln ur_i$	0.068	0.000	0.100	0.037	-0.020	-0.003	-0.022	-0.021
	(0.142)	(0.996)	(0.123)	(0.252)	(0.715)	(0.959)	(0.581)	(0.680)
cl_i	-0.524^{*}	0.218	0.000	-0.070	1.518^{***}	0.000	0.000	0.000
	(0.090)	(0.291)	(0.000)	(0.573)	(0.000)	(0.000)	(0.000)	(0.000)

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	DE	FR	IT	MA	NL	PL	TR	TOT
$W \ln sf_i$	−1.533	3.103**	−7.016***	0.502	−1.684	0.113	−0.677	−0.008
	(0.231)	(0.021)	(0.000)	(0.536)	(0.282)	(0.921)	(0.541)	(0.995)
$W \ln pd_i$	−0.473	6.028***	−9.563***	1.754*	−1.779	3.240**	−1.891	2.313
	(0.784)	(0.000)	(0.000)	(0.085)	(0.296)	(0.019)	(0.177)	(0.114)
$W \ln dbo_i$	−0.277**	−0.626***	−0.281	−0.169**	−0.356***	−0.053	−0.200	−0.555***
	(0.011)	(0.000)	(0.046)	(0.015)	(0.009)	(0.632)	(0.082)	(0.000)
$W \ln dbr_i$	0.472	−0.809**	−2.199***	−0.170	0.288	−0.393	−0.980***	−0.545**
	(0.169)	(0.014)	(0.000)	(0.447)	(0.312)	(0.169)	(0.000)	(0.042)
$W \ln ho_i$	2.344	13.467***	−0.998	1.645	−0.603	2.811*	−0.543	5.201***
	(0.146)	(0.000)	(0.669)	(0.113)	(0.743)	(0.072)	(0.688)	(0.001)
$W \ln sc_i$	−1.742	−7.487***	−1.260	0.650	−0.072	0.843	1.871*	−3.842***
	(0.111)	(0.000)	(0.428)	(0.429)	(0.959)	(0.477)	(0.064)	(0.002)
$W \ln sp_i$	−0.210***	0.004	−0.050	0.078	0.334	−0.073	0.026	0.052
	(0.000)	(0.978)	(0.461)	(0.337)	(0.246)	(0.104)	(0.522)	(0.224)
$W \ln mw_i$	0.211	0.293	0.190	0.043	1.001***	−0.207	0.338*	1.271***
	(0.302)	(0.130)	(0.508)	(0.744)	(0.000)	(0.244)	(0.067)	(0.000)
$W \ln to_i$	0.018	0.122	0.196**	−0.105	0.180	0.224***	−0.020	0.410***
	(0.840)	(0.214)	(0.052)	(0.099)	(0.111)	(0.004)	(0.768)	(0.000)
$W \ln ur_i$	−1.070	−1.781**	3.609**	−2.056***	0.940	−2.859***	−0.606	−0.113
	(0.261)	(0.047)	(0.012)	(0.001)	(0.324)	(0.000)	(0.488)	(0.887)
$W cl_i$	9.136***	−1.965	0.000	−0.763	3.805	0.000	0.000	0.000
	(0.001)	(0.270)	(0.000)	(0.515)	(0.295)	(0.000)	(0.000)	(0.000)
$W \hat{\alpha}_i$	0.939***	0.999***	0.914***	0.853***	1.000***	0.951***	0.261	0.995***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.590)	(0.000)
Adj R^2	0.5863	0.6039	0.6278	0.808	0.6906	0.6099	0.6951	0.5858
LL	−109.64425	−245.92949	−260.75361	65.118331	−221.58189	−168.5815	−11.56572	−203.34322

Note: *P*-values in parenthesis are calculated using simulated standard errors based on 1000 bootstrap samples. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively.

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